Proximal soil sensors and data fusion for precision agriculture

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Dedicated to my beloved Mother, late Father and highly esteemed Supervisors!

Chapter 1

General introduction

1.1. Background

Soil is the foundation of life in terrestrial ecosystems and its quality not only affects the ecosystem productivity, it also plays a crucial role in environmental issues and has an impact on the energy budget for farming. Due to an ever increasing global population, agricultural land has been lost to urbanisation and industrialisation. In addition, a vast land area is turned into deserts every year due to soil degradation, water scarcity, erosion and salinity issues (Godfray et al., 2010).

Qualitative and quantitative knowledge of soil properties is very important for well-founded decision making for growing crops. For instance, soil texture is directly or indirectly critical in developing recommendations concerning soil cultivation, sowing and base fertilisation. Numerous soil properties and processes are influenced by texture, such as water holding capacity, aeration, erosion, soil tillage, pH buffering capacity, etc. Soil structure has a major influence on water and air movement, biological activity, root growth and seedling emergence. Soil water undoubtedly is essential for plants and soil organic matter plays a major role in the buffering and release of nutrients, which improves the water holding capacity of soil and strongly influences the biological activity in the soil. Soil salinity may disrupt the normal osmotic balance in plant roots. Soil fertility, the capacity to retain nutrients in the soils and to make these available to the plant is, apart from the organic matter status, also influenced by soil pH. From a physical point of view, soil density and soil strength affect the ability of roots to penetrate the soil and influence the workability of a soil (McLaren and Cameron, 1996).

From the above example, it is clear that soil is a heterogeneous system whose processes and mechanisms are complex and difficult to fully comprehend (Viscarra Rossel et al., 2006). Soils are susceptible to significant spatial variability and variations occur over short distances, vertically and horizontally. Spatial variability in soil properties is due to a complex interaction of biological (e.g. earthworms, pests and microbes), edaphic (e.g. salinity, organic matter, nutrients and texture), anthropogenic (e.g. soil compaction due to farm machinery), topographic (e.g. slope and elevation) and climatic (temperature, relative humidity and rainfall) factors (Corwin and Lesch, 2005).

Production of agricultural crops is a complex system of the interaction of seed, soil, water, agro-chemicals and fertilisers. Sensible management of all these inputs, therefore, is essential for the sustainability of such a complex system.

1.2. Precision agriculture

The conventional soil management systems were and still are based on the use of generalised recommendations across the whole field or even in all the fields of a farm or region. Variations in soil characteristics, such as texture, structure, fertility status, moisture retention, topography, plant growth and pest and weed populations, as they occur both in time and spatially, are ignored. Usually differences are known to the farmers, but lack of proper tools prevents effective use of this information as a basis for specific management application. This would result in over-application of inputs in some zones of a field and under-application in others leading to a decrease in yield and quality. The development and

availability of novel technologies now allows farmers to address this issue and implement precision agriculture systems.

Precision agriculture is an information- and technology-based farm management system that aims at the application of technologies and principles to identify, analyse and manage spatial and temporal variability associated with all aspects of agricultural production within fields for near-optimal profitability, sustainability, improving crop performance, protecting land resources and safeguarding the environment (Pierce and Nowak, 1999; Zhang et al., 2002). Aspects of precision agriculture therefore cover a broad array of topics, such as characterising variability in soil resources, weather, crop diversity, machinery performance, plant genetics and crop physical, chemical and biological inputs (Pierce and Nowak, 1999). Therefore, precision agriculture is a multidisciplinary approach.

The concept of precision agriculture is based on the variability in those soil, crop and environmental attributes. Characterisation of soil physical, chemical and biological properties is one of the important topics in the domain of precision agriculture, which is directly or indirectly linked with many other applications, such as site-specific application of fertilisers, irrigation, manure and other inputs, delineating management zones, sensing plant stresses, soil tillage, crop performance, mapping slope, topography and other attributes, yield monitoring and machinery performance. Sensing and mapping of soil factors provide decision support information to the crop manager in identifying factors limiting to growth and yield in various parts of the field.

Thus, basic steps in precision agriculture are sensing variability, managing variability and evaluating the decisions based on the management of variability (Pierce and Nowak, 1999). Sensing variability is the most critical step in precision agriculture because proper management cannot be done without proper knowing. After adequately assessing variability, it can potentially be managed by matching required inputs in spatial and temporal context.

Sensing or mapping soil, crop and environmental attributes generates large quantities of data for the crop manager to deal with. Data overloading problems can be solved by introducing engineering innovations by integrating the data, developing expert systems and decision support systems (Stafford, 2000). Furthermore, developing new sensors capable of rapidly sensing required information is another engineering domain needed to make precision agriculture feasible for agricultural practice.

The fundamental components of precision agriculture include high resolution global positioning system (GPS) devices, remote sensing (for example, aerial photography, satellite and airborne multispectral imagery, microwave and hyper-spectral imagery, radiometrics and geophysical sensing), yield monitors, variable-rate technologies and proximal soil sensors (for example, electromagnetic induction, visible-near infrared spectroscopy and dielectric sensors) (Plant, 2001).

The focus of this study is soil sensing using proximal soil sensors with the objective to bring precision agriculture one step further to practice by proper selection of sensors and assessing the potential of their complementary data fusion.

1.3. Conventional soil sampling and laboratory analysis

To get an understanding about the complex soil system and to assess its quality, laboratory soil analyses have been used as tools since years for use in conventional soil management and have been thought to be reliable and effective to increase crop productivity. Nevertheless, collection of fine-scale information on soil properties, using conventional soil sampling and laboratory methods, is time consuming, laborious and expensive (Viscarra Rossel and McBratney, 1998b). Sampling density is also not sufficient to decipher small scale spatial variations within a field due to the point sampling procedure. Therefore, the development of alternative methods for attaining this information is crucial (Viscarra Rossel and McBratney, 1998a). The outcome of laboratory analysis is still taken as a basis for reference, ignoring the fact that variations amongst the laboratory results may also be serious.

1.4. Proximal soil sensors

Proximal soil sensors in precision agriculture are ground-based sensors to obtain signals either with a direct contact with soils or from a close distance (within 2 m) (Viscarra Rossel et al., 2011). The soil sensors detect the physical measures of soil that correspond and relate to different soil properties. Proximal soil sensors may be described by the manner in which they measure (invasive (in-situ or ex-situ) or non-invasive), the source of their energy (active or passive), how they operate (stationary or mobile) and the inference used in the measurement of the target soil property (direct or indirect) (Viscarra Rossel et al., 2011).

Advances in remote and proximal soil sensing methods have made it possible to rapidly acquire large volumes of soil and crop data. Data from remote sensing methods, such as from a satellite suffer from inadequate spatial and temporal resolution (McBratney et al., 2003) and crop residue cover and other limitations of remote sensing (timeliness, cost and lack of processing of data) limit the use of aerial and satellite soil imagery. It is expected that using proximal sensors, less ambiguous relations can be established between sensor and soil property data (Barnes et al., 2003). Proximal soil sensors have the capability to rapidly collect inexpensive high-resolution soil data and even in real-time, by taking measurements as frequently as once every second (Viscarra Rossel and McBratney, 1998b) and to identify variations in soil properties. These soil sensors can scan soils with spatially dense measurements, although their outcome may not be as accurate as of the laboratory methods (Minasny and McBratney, 2002), due to environmental factors, sensing volume, mismatching of sensing and sampling spots and difference in sensing and sampling time (Mouazen et al., 2007). Sudduth et al. (2005) reported that soil analysis based on soil sensors used in precision agriculture provides several advantages over conventional laboratory methods, such as lower cost, increased efficiency, more timely results and collection of dense datasets while just traversing a field. The dense datasets, as compared with the conventional sampling methods, increase the overall spatial estimation accuracy even if the accuracy of individual measurements is lower (Minasny and McBratney, 2002). Sensors providing quantitative results are becoming smaller, faster, more accurate, more energy efficient, wireless and more intelligent.

Proximal soil sensors can be divided into five main categories based on their sensing concept (Kuang et al., 2012) (Figure 1.1). Based on the way sensors are used in precision agriculture, they can be divided into two general categories: reactive and predictive. A reactive (real-time) sensor is used to change the rate of application of an input in response to local conditions at the time of application. In contrast, a predictive (map-based) sensing system is used to acquire the data and to generate soil property maps off-site after processing and interpreting the data followed by decision-making about the optimal use of agricultural inputs (Adamchuck et al., 2011). The reactive methods do not have widespread feasibility due to their complexity of design and seem less optimal if the spatial distribution of a sensed soil property (e.g. apparent soil electrical conductivity) does not change during the growing season. The predictive methods have more widespread utilisation in precision agricultural applications.

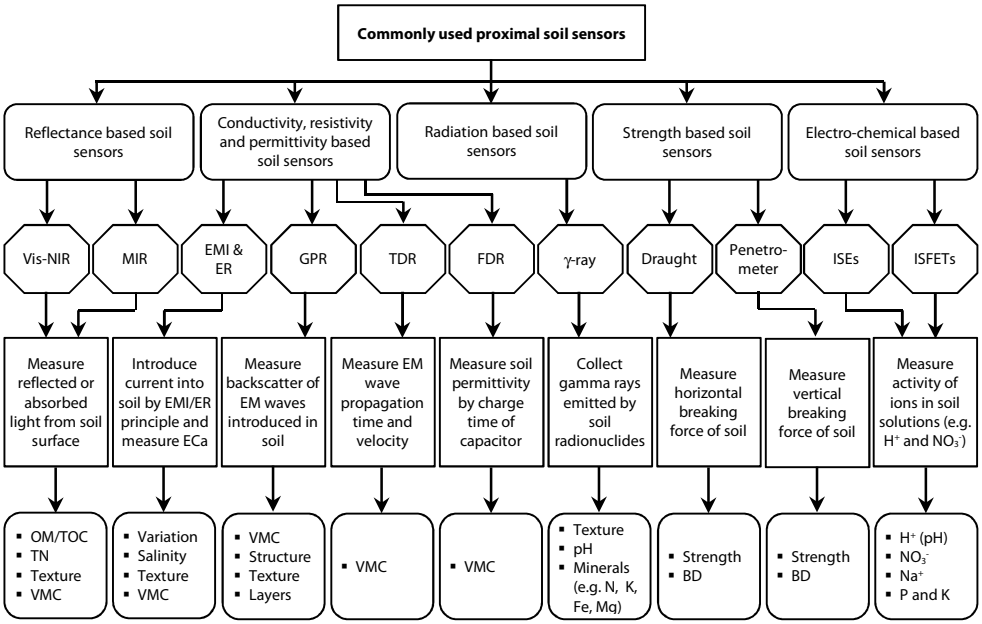

Figure 1.1. *Classification of commonly used proximal soil sensors as described in Kuang et al. (2012). Abbreviations: Vis-NIR = visible-near infrared; MIR = mid-infrared; EMI = electromagnetic induction; ER = electrical resistivity; GPR = ground penetrating radar; TDR = time domain reflectometry; FDR = frequency domain reflectometry; ISEs = ion-selective electrodes; ISFETs = ion-sensitive field-effect transistors; ECa = apparent soil electrical conductivity; OM = organic matter; TOC = total organic carbon; VMC = volumetric moisture content; BD = bulk density and TN = total nitrogen.*

1.5. Scope and motivation

Quite a number of proximal soil sensors are being used for characterising soil properties (Figure 1.1). Selection of a proper sensor for characterising a specific soil property with certainty is very difficult for a farm manager for site-specific soil management. Adamchuk et

al. (2004) evaluated many on-line (real-time) soil sensing methods discussing their advantages and disadvantages. Nevertheless, in literature more focus has been given on in-situ and laboratory methods for soil sensing. Therefore, evaluation of proximal soil sensors used in laboratory, in-situ and on-line is very important and will help in selection of a suitable soil sensor to characterise a specific soil property.

Accuracy of a single soil sensor is often not optimal because virtually all available soil sensors can respond to more than one soil property of interest (Adamchuck et al., 2011). A sensing technique that is supposed to provide information about one soil parameter is considered of limited use when the environmental and other soil characteristics or conditions, such as rainfall, soil temperature, soil particle size or aggregation, chemicals in the soil solution and many others disturb the output. This makes the interpretation of corresponding relationships between sensor output and a soil parameter more complex and uncertain (Mahmood et al., 2009). It is postulated that this inability of single-sensor based systems can be overcome by combining conceptually different sensing methods and subsequently integrating the results. This will hold promise for providing complementary and more robust soil property estimates and will lead to increased adoptability of sensor based crop management (Adamchuck et al., 2011; Mahmood et al., 2009; Mouazen, 2009).

Data fusion or integration techniques combine data from different sensors or sources together. Data fusion is an important tool that may improve the performance of a detecting system when various complementary sensors are available. The aim of a data fusion approach is to obtain target information with better quality and reliability (Mahmood et al., 2009). Data fusion may perform inferences that are more effective and potentially more accurate than if they were achieved by a single sensor. The general process of complementary data fusion is shown in Figure 1.2.

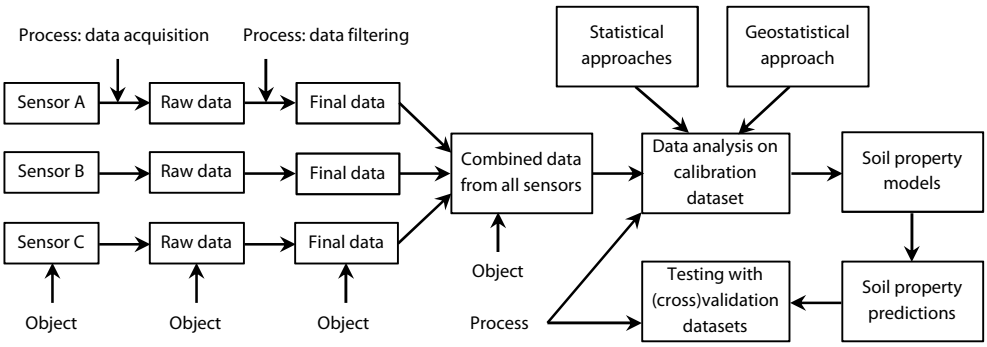

Figure 1.2. *Schematic of complementary data fusion process used in this thesis.*

1.6. Objectives, research questions and outline of this thesis

The ultimate and high-level objective of this thesis is to bring sensor-based precision agriculture one step further. To accomplish this, the following objectives were formulated:

- To evaluate different proximal/ground-based soil sensors used in laboratory, in-situ and on-line in their capacity of quantifying soil properties.
- To assess the potential of data fusion of multiple sensors to predict various physical and chemical soil properties.

For data fusion, we restricted our research to three soil sensors: an EM38, a vis-NIR spectrometer and a gamma-ray spectrometer. The EM38 is a technology that measures the ability of soil to conduct electric current based on the principle of induction and reflection of a magnetic field. The vis-NIR technology uses the reflection and absorption properties of soil (constituent) in the visible and near infrared part of electromagnetic spectrum. The gamma-ray approach measures the emission of naturally occurring radioisotopes from the soil surface. The reason for adopting these sensors is threefold. First of all, based on a literature study, these sensors were found to be most promising and readily available. Secondly, these sensors can measure more than one soil property. Finally, these sensors can measure some common soil properties directly, e.g. clay content.

When trying to fulfil the above objectives and bring the field of sensor based precision agriculture a step forward, quite a few knowledge gaps need to be bridged. Some of these are identified and explained below. To fill the knowledge gaps and fulfil the objectives stated above, research questions are formulated followed by the outline of the thesis.

Precision agriculture literature is lacking a comprehensive review covering different proximal soil sensors and evaluating the accuracy of each sensing method. To fill this gap, the formulated research question is:

i. What methods and technologies are available for soil sensing and which of these are suitable for use in precision agriculture to support the management of the soil-water-plant system?

Chapter 2 discusses this research question, where different proximal soil sensing methods are presented as used in the laboratory, in-situ and on-line for estimating key soil properties in precision agriculture. The most relevant literature of each sensing method is reviewed, sensing principles are described as well as environmental factors affecting their output, potentials and limitations are discussed as well as future scope and possibilities of data fusion. The most accurate sensing methods to measure a certain soil property for a given application are highlighted. Sensors are also discussed in view of future farming applications, considering aspects, such as accuracy, site-specific tillage operation, modelling crop growth and yield and carbon sequestration.

Vis-NIR reflectance spectroscopy is a robust soil sensing method for precision agriculture. Local calibration (e.g. models of an individual field or fields) of vis-NIR spectroscopy yields very good soil property estimates often comparable to conventional laboratory methods. Nevertheless, local calibration of vis-NIR spectroscopy is not practical because it requires a considerable number of samples and time. Therefore, other modelling strategies, such as general (e.g. combining some proportion of samples from all available fields), spiked (e.g. including a few samples from the target field in the set of all samples from other fields) and true validation (e.g. prediction in an independent field) models, need to be adopted on field-scale studies. Evaluation of vis-NIR spectroscopy and comparing the effectiveness of these

modelling strategies in a field scale has not been studied so far. This knowledge gap gives rise to the following research questions:

ii. How robust are the local, general, spiked and true validation models of vis-NIR spectroscopy when used to predict soil properties at field level?
iii. Can general, spiked and true validation models of vis-NIR spectroscopy help improve the soil characterisation and significantly reduce expenditure and time to achieve this?

The answers to above two questions are discussed in Chapter 3. The robustness of vis-NIR reflectance spectroscopy is evaluated using various calibration approaches: local calibration, general calibration, spiked calibration and leaving entire field out calibration (or independent field validation). The data for this study are collected in five fields in the Netherlands, different in texture and soil properties. The local models contain samples of individual fields, whereas the general models are made by combining different proportions of samples from all fields. The spiked models are made using all samples from four fields and 10 samples from the target field. Similarly, in true validation, we make calibration models from four fields and predict soil properties in the remaining (target) field. The evaluation of these modelling strategies is done by predicting soil texture (clay, silt and sand), pH, EC, total organic carbon (TOC) and total nitrogen (TN) in individual fields.

Proximal gamma-ray spectroscopy is an emerging soil sensing method in precision agriculture. Most studies in literature are focussed on developing relationships between radiometric data and soil properties. Prediction of soil properties using developed relationships has not been widely studied. Furthermore, there is a debate whether we should use complex data filtering and de-noising algorithms to analyse the data by considering full spectrum or we should simply rely on the conventional method of energy windows. So far, the potential of two calibration methods: energy windows and full-spectrum has not been assessed to predict soil properties using gamma-ray spectroscopy. Here, following research questions will be addressed:

iv. What is the potential of gamma-ray spectroscopy to estimate various soil properties?
v. Can the full-spectrum analysis of gamma-ray data yield better predictions than the conventional windows method in gamma-ray spectroscopy?

Chapter 4 evaluates the potential of a proximal gamma-ray spectrometer to predict several soil properties in two soil depths (0-15 cm and 15-30 cm) and in two sandy loam fields. Two data analysis methods, energy windows and full-spectrum analysis, are compared to predict soil texture, EC, pH, TOC and TN.

Sensor data fusion has received substantial attention in research areas (aerospace, information technology, etc.), but it is a new topic of research in precision agriculture. So far very few reports are found in scientific literature on this topic providing a reference for fusion of data from complementary sensors from soils in a field situation. There is no research evidence that can provide clues about the best statistical data handling and analysis methods for sensor data fusion to achieve the maximum benefit from this approach. In the same sense, the potential of geostatistics for data fusion of multiple sensors for soil property

mapping has neither been studied so far. To fill this knowledge gap, the following research questions will be addressed:

vi. What is the effectiveness of data fusion in precision agriculture; can we achieve a better accuracy of predictions fusing the outputs of two or more sensors?
vii. How do different statistical approaches for data fusion perform, and which one can be used for best results?
viii. What is the potential of geostatistics for performing data fusion of multiple sensors?

Chapter 5 deals with the complementary data fusion of an EM38 and a vis-NIR spectrometer. Data fusion results are compared with those of individual sensors. Furthermore, three data analysis methods are compared for data fusion: stepwise multiple linear regression, partial least squares regression and principal components analysis combined with stepwise multiple linear regression. The comparison of fusion methods is made to predict clay, silt, sand, EC, pH, TOC and TN in three different fields.

In Chapter 6, data fusion is discussed using geostatistics. The data of three sensors: vis-NIR spectrometer, EM38 and gamma-ray spectrometer are combined as covariates. The significance of geostatistics for data fusion for clay mapping is assessed.

Finally, Chapter 7 contains a general discussion, main findings and suggestions for future work.

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Chapter 2

Sensing soil properties in the laboratory, in-situ and on-line – A review

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* *These authors contributed equally in this review article.*

2.1. Abstract

Since both the spatial and vertical heterogeneities in soil properties have an impact on crop growth and yield, accurate characterisation of soil properties at high sampling resolution is a preliminary step in successful management of soil-water-plant system. Conventional soil sampling and analyses have shown mixed economical returns due to the high costs associated with labour-intensive sampling and analysis procedures, which might be accompanied with map uncertainties. Therefore, the conventional laboratory methods are being replaced or complemented with the analytical soil sensing techniques. The objective of this paper is to review different soil sensing methods used to characterise key soil properties for management of soil-water-plant system. This will cover laboratory, in-situ in the field and on-line measurement methods. This review article is furnished with an overview of background information about a sensing concept, basic principle and brief theory, various factors affecting the output of the sensor and justification of why specific soil properties can be related with its output. The literature review is succeeded with an integration and analysis of findings in view of application in the precision agriculture domain. Potentials and limitations of current sensor technologies are discussed and compared with commonly used state-of-the art laboratory techniques. As sensing is commonly addressed as a very technical discipline, the match between the information currently collected with sensors and those required for site specific application of different inputs and crop growth and development is discussed, highlighting the most accurate method to measure a soil property for a given application.

Keywords: Soil properties; Precision agriculture; ground-based soil sensors; evaluation of sensors; a review.

2.2. Introduction

Soil, a layer of natural material on the earth's surface, is composed of both organic and inorganic substances and is the key resource in crop production. Soils are heterogeneous in nature as a result of parent material, weathering history and landscape. This becomes apparent in their physical and chemical properties, nutrient availability and many other factors. Spatial variability in soil properties is due to a complex interaction of biological (e.g. earthworms, pests, microbes), edaphic (e.g. salinity, organic matter, texture), anthropogenic (e.g. soil compaction due to farm machinery, structure as a result of tillage), topographic (e.g. slope, elevation) and climatic (temperature relative humidity, rainfall) factors (Corwin and Lesch, 2005a). Accurate characterisation of soil is a prerequisite in successful management of the soil-water-plant system.

Precision agriculture is a site-specific management method explicitly taking within field variation of soil and crop into consideration. It is a technology driven system that provides spatial and temporal information (where, how much and when to apply) about the application of farm inputs such as tillage, irrigation, fertilisers, pesticides, etc. in a field (Corwin and Lesch, 2005a; Gebbers and Adamchuk, 2010; Pierce and Nowak, 1999). Knowledge on within field variability is essential for the successful implementation of precision agriculture (Bullock and Bullock, 2000). However, recommendation on application of different inputs into soils, until recently, considered agricultural fields as uniform elements, despite the presence of within field spatial variability. Ignoring this variability can result in poor land and crop management, leading to yield losses or inefficient use of inputs. Apart from the costs associated with excess use of chemicals, for examples, fertilisers, pesticides and herbicides, the environmental impact is also considerable due to the increased contamination of water resources. Despite significant progress, the lack of technology to determine within field soil characteristics rapidly and in a cost effective manner is still one of the biggest obstacles for successful implementation of precision agriculture (Adamchuk et al., 2004a). Characterisation of soil variability at field or subfield scale using conventional methods is a labour intensive, very expensive and time consuming procedure, particularly when high resolution data is required. Therefore, for precision agriculture, new soil sensors and sensing concepts are needed to characterise within field variability to allow for efficient site-specific soil management.

Remote sensing data collection by airplane or satellite is a promising approach that received considerable attention in the past decade (Mulder et al., 2011). It is an approach that is contactless and does not require access to the field. Yet, it still suffers from inadequate spatial and temporal resolution (McBratney et al., 2003) and interference from clouds and crop residue cover. It is therefore expected that the precision agriculture approach will have to rely on data obtained in the field for times to come.

Potentially, proximal or ground-based (invasive or non-invasive) soil sensors have the ability to collect high resolution data rapidly and in certain cases even allowing real-time analysis and processing, by taking measurements as frequently as one per second (Viscarra Rossel and McBratney, 1998). Sensor-based soil analysis potentially provides several advantages

over conventional laboratory methods such as lower cost, increased efficiency, more timely results and collection of dense datasets while just traversing a field.

Earlier reviews have provided some insight into the availability and characteristics of various sensing principles for precision agriculture applications. Adamchuk et al. (2004a) provided a comprehensive review of technologies used only for on-line measurement systems of soil properties. This paper did not attempt to link between the physical principles of the sensing methods and the successful/unsuccessful measurement of a soil property. A recent review article by Sinfield et al. (2010) evaluated the sensing technologies for on-line detection of soil macro-nutrients, for example, nitrogen, phosphorus and potassium, whereas Lee et al. (2010) reviewed the sensing technologies for precision crop production, with emphasis on crop and canopy mapping. To our knowledge, none of these papers attempted to cover sensing methods used in the laboratory, in-situ and on-line. As a matter of fact, the evaluation of accuracy under these three conditions for the measurement of a soil property, as compared to the accuracy obtained with traditional laboratory methods of soil analysis has not been reported so far. Finally, sensing is usually addressed as a purely technical discipline. Yet, to make precision agriculture works in practice, sensing principles and the information sensors produce should match the information required for precision agriculture. To the best of our knowledge, this aspect has hardly ever been discussed.

The outline of this article is as follows. The article reviews the ground based soil sensing methods used to characterise key soil properties and evaluates the accuracy of these methods under laboratory, in-situ and on-line measurement conditions. The potential of a multi-sensor and data fusion approach to improve the information extracted from collected data will be addressed. Finally, current sensor technologies will be discussed in view of its ability to identify and evaluate suboptimal soil conditions requiring treatment or inputs in order to optimise crop growing conditions.

2.3. Soil sensors

Adamchuk et al. (2004a) categorised different on-line soil sensors in six main categories based on their design concepts, including electrical and electromagnetic, optical and radiometrics, mechanical, acoustic, pneumatic and electrochemical soil sensors. The authors added that the output of majority of the soil sensors is affected by more than one agronomic soil characteristic. Since we emphasise on explaining the fundamentals of successful measurement of a soil property with a sensing technique, the following five categories are suggested for laboratory, in-situ and on-line measurement conditions:

1. Reflectance based soil sensors
2. Conductivity, resistivity and permittivity based soil sensors
3. Passive radiometric based soil sensors
4. Strength based soil sensors and
5. Electro-chemical based soil sensors

Due to different soil types, parent materials, soil and environmental factors, for example, water content, temperature, humidity, organic matter, topography and soil colour, the performance of different sensors varies considerably with mixed results reported.

2.3.1. Reflectance based soil sensors

To generate a soil spectrum, radiation containing all relevant frequencies in the particular range is directed to the sample. Depending on the constituents present in the soil the radiation will cause individual molecular bonds to vibrate, either by bending or stretching. These vibrations lead to absorption of light, to various degrees, with a specific energy quantum corresponding to the difference between two energy levels. As the energy quantum is directly related to frequency, the resulting absorption spectrum produces a characteristic shape that can be used for analytical purposes (Stenberg et al., 2010). The fundamental vibrations in the mid-infrared (MIR) region result in overtones and/or combinations in the near infrared (NIR) region. In the visible (vis) range (400–780 nm), absorption bands related to soil colour are due to electron excitations, which assist the measurement of soil organic matter content (SOM) and moisture content (MC). However, in the NIR range, the overtones of OH and overtones and/or combinations of C-H + C-H, C-H + C-C, OH^+ minerals and N-H are important for the detection of SOM, MC, clay minerals and nitrogen (Mouazen et al., 2010).

2.3.1.1. Visible-near infrared sensors

During the early stage of implementing this technique for soil analysis, the vis-NIR (400-2500 nm) spectroscopy, along with multiple linear regression (MLR) calibration technique, was used to determine some soil properties, such as soil MC, SOM, total carbon (TC), inorganic carbon (C_{in}), organic carbon (OC), pH, cation exchange capacity (CEC) and total nitrogen (TN). As early as from 1965, Bowers and Hanks (1965) used a NIR spectrophotometer to evaluate the influences of MC, SOM and particle size on energy reflectance.

With the emerging of commercial NIR spectrophotometers and multivariate calibration software packages, the vis-NIR spectroscopy has been adopted much widely for soil analysis. Numerous researchers have extended the vis-NIR spectroscopy applications from the measurement of key soil properties (MC, pH, SOM, TN and OC) with high accuracy to almost all other micro and macro elements with less accuracy. The analysis of soil with this technique was also extended to soil biological, physical and engineering properties. Multivariate calibration techniques allowed for simultaneous measurements of several soil properties under consideration.

2.3.1.1.1. Laboratory visible and near infrared spectroscopy

Laboratory vis-NIR measurement needs minimal sample pre-treatments and is subjected to minimum outside interferences. A typical procedure in a laboratory includes soil sampling, sample treatments (drying, grinding and sieving), optical scanning, data pre-processing, calibration and validation. Drying and grinding of soil samples can minimise the negative effects of MC and structure on the accuracy of prediction.

2.3.1.1.1.1. Soil properties with direct spectral responses in near infrared range

Since carbon and nitrogen have both direct spectral responses in the NIR region, which can be attributed to overtones and combinations of N-H, C-H + C-H and C-H + C-C, successful

measurement of these two properties with NIR is expected. However, C and N have different forms in the soil, for example, mineral, organic and inorganic, which have an influence on the accuracy. Summary of measurement accuracy of C and N with vis-NIR spectroscopy is provided in Table 2.1. Chang et al. (2001) found TC, TN and MC to be readily and accurately estimated (R^2 > 0.84; ratio of prediction deviation (RPD) > 2.47). Reeves and McCarty (2001) also reported successful estimation of TC (R^2 = 0.92; root mean square error (RMSE) = 0.15 %) and TN (R^2 = 0.90; RMSE = 0.0132 %). However, mineral nitrogen, for example, ammonia and nitrate are very difficult elements to be measured with NIR (Stenberg et al., 2010) and only few reports showed successful cases (e.g. Shibusawa et al., 2001). In summary, the prediction of soil C and N with NIR depends upon the form to be measured and the most successful measurement is reported for the organic, inorganic and total forms (Table 2.1). Due to the obvious absorbance peaks in the NIR range at the 1st, 2nd and 3rd overtone regions, literature proves MC to be the most accurately measured property with NIR with excellent accuracy (Chang et al., 2001; Mouazen et al., 2006b). Clay content was also reported to be accurately measured with NIR, which is attributed to the direct spectral response of clay minerals around 2300 nm (Viscarra Rossel et al., 2006).

Table 2.1. *Summary of measurement accuracy of soil fundamental properties by laboratory visible and near infrared (vis-NIR) Spectroscopy*

Soil properties	R^2 [a]	RMSEP	RPD	Accuracy	Key references
OC	0.46-0.98	0.06-2.90 (%)	1.30-9.70	A [b]	Dalal and Henry (1986); Chang et al. (2001); Shepherd and Walsh (2002); Viscarra Rossel et al. (2010).
C_{inorg}	0.53-0.96	0.17-0.56 (%)	4.01-4.99	A	Krishnan et al. (1980); Cohen et al. (2005); Brown et al. (2006); Fontán et al. (2010).
TN	0.04-0.99	0.0004-0.08 (%)	0.34-6.80	A	Coûteaux et al. (2003); Dalal and Henry (1986); Vagen et al. (2006); Guerrero et al. (2010).
pH	0.50-0.97	0.04-1.43	0.57-2.39	B-C	Shepherd and Walsh (2002); Cohen et al. (2005); Mouazen et al. (2006a); Viscarra Rossel et al. (2010).
Ca	0.07-0.95	0.66-52.90 (cmol kg^{-1})	0.60-2.75	B	Cozzolino and Morón (2003); Cohen et al. (2005); Mouazen et al. (2006a); Zornoza et al. (2008).
CEC	0.13-0.90	1.22-10.43 (cmol kg^{-1})	0.55-2.51	B	Ben-Dor and Banin (1995); Chang et al. (2001); Mouazen et al. (2006a); Brown (2007); Awiti et al. (2008).
Clay content	0.15-0.91	0.79-6.10 (%)	1.70-3.10	A	Ben-Dor and Banin (1995); Chang et al. (2001); Brown (2007); Awiti et al. (2008).

Sand content	0.59-0.92	1.91-11.93 (%)	0.87-3.40	C	Ben-Dor and Banin (1995); Chang et al. (2001); Cozzolino and Morón (2003); Awiti et al. (2008).
Silt content	0.41-0.84	1.79-9.51 (%)	1.09-3.07	C	Ben-Dor and Banin (1995); Chang et al. (2001); Cozzolino and Morón (2003); Awiti et al. (2008).
MC	0.84-0.98	0.50-4.88 (%)	2.36-5.26	A	Chang et al. (2001); Chang et al. (2005); Dalal and Henry (1986); Mouazen et al. (2006b); Slaughter et al. (2001).
Total P	0.01-0.93	1.35-24.6 (100 mg kg^{-1})	0.10-3.80	C	Bogrekci and Lee (2005b); Mouazen et al. (2010); Wetterlind et al. (2010).
P_{avl}	0.68-0.95	0.01-19.79 (100 mg kg^{-1})	1.70-4.54	C	Bogrekci and Lee (2005b); Cohen et al. (2005); Ludwig et al. (2002).
P_{ext}	0.32-0.77	1.70-3.89 (100 mg kg^{-1})	0.40-2.07	C	Chang et al. (2001); Cohen et al. (2005); Udelhoven et al. (2003).
Mg	0.53-0.91	0.03-38.36 (cmol kg^{-1})	0.48-2.54	B	Cozzolino and Morón (2003); Van Groenigen et al. (2003); Udelhoven et al. (2003); Wetterlind et al. (2010).
K	0.11-0.85	0.05-1.84 (cmol kg^{-1})	0.52-5.13	D	Cozzolino and Morón (2003); Van Groenigen et al. (2003); Mouazen et al. (2006a).
Na	0.09-0.68	2.3-25 (cmol kg^{-1})	0.92-1.94	E	Chang et al. (2001); Mouazen et al. (2006a); Mouazen et al. (2010).

[a] Values of R^2, RMSEP and RPD do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

[b] Classification of accuracy into A, B, C, D and E was based on maximum number of publications confirming an accuracy category for a soil property. R^2: coefficient of determination, RMSEP: root mean square error of prediction, RPD: residual prediction deviation (SD/RMSEP), A: excellent (RPD > 3.0 and R^2 > 0.90; B: good (RPD = 2.5~3.0 and R^2 = 0.82~0.90), C: approximate quantitative prediction (RPD = 2.0~2.5 and R^2 = 0.66~0.81), D: distinguish between high and low (RPD = 1.5~2.0 and R^2 = 0.50~0.65) and E: not usable (RPD < 1.5 and R^2 < 0.5) (Chang et al., 2001).

2.3.1.1.1.2. Soil properties without direct spectral responses in NIR range

Stenberg et al. (2010) concluded that occasionally successful reports for the measurement of soil properties without direct spectral response in the NIR range is due to co-variation through other properties that have direct spectral responses in the NIR, for example, carbon, nitrogen and clay. Literature illustrates that only few successful reports on phosphorous (P) determination by vis-NIR spectroscopy are available (Table 2.1). To date, the most significant reports on successful measurement of P are those of Bogrekci and Lee (2005a; 2005b). Bogrekci and Lee (2005a) obtained probably the best R^2 value of 0.92 between P concentrations and spectral absorbance using a vis-NIR spectroscopy in a fine sand soil type in Lake Okeechobee, in Florida. When they collected a larger amount of samples (150 - 345

samples) from more sites (3 - 10 sites), they reported a better prediction result (Bogrekci and Lee, 2005b). Literature, e.g. Chang et al. (2001) and Mouazen et al. (2006a) proves that the worst properties to be measured with NIR are K and Na (Table 2.1). Measurement of pH, Ca and Mg were reported to be more successful as compared to K and Na, but underperformed those properties with direct spectral response in NIR. Therefore, further research is recommended to understand and probably improve the calibration accuracy of soil properties without direct spectral responses in the NIR range.

2.3.1.1.1.3. Soil heavy metals

Literature demonstrates the potential of the vis-NIR spectroscopy for the measurement of soil microelements with acceptable accuracy (Table 2.2). Morón and Cozzolino (2003) explored the use of NIR reflectance spectroscopy to study microelements in surface soils from 332 sites across Uruguay. They claimed that R^2 of the calibration and standard error of cross-validation (SECV) were respectively for Cu 0.87 and 0.7, Fe 0.92 and 21.7, Mn 0.72 and 83.0 and Zn 0.72 and 1.2 on mg kg^{-1} dry matter. Siebielec et al. (2004) employed the NIR spectroscopy to measure soil metal content from natural background levels to high contents indicative of industrial contamination region and they claimed successful measurement of Fe, Cu, Ni and Zn (R^2 = 0.87, 0.61, 0.84 and 0.67, respectively).

Table 2.2. *Summary of measurement accuracy of soil microelements by laboratory visible and near infrared (vis-NIR) Spectroscopy*

Soil properties	R^2 [a]	RMSEP (mg kg^{-1})	RPD	Accuracy	Key references
Fe	0.64-0.94	3.7-23.60	1.35-3.30	A-B [b]	Malley and Williams (1997); Morón and Cozzolino (2002); Cohen et al. (2005).
Cu	0.25-0.84	0.8-6.01	0.92-4.00	B	Malley and Williams (1997); Chang et al. (2001); Siebielec et al. (2004); Wu et al. (2007).
Mn	0.65-0.92	56.4-190	1.79-3.66	C	Malley and Williams (1997); Chang et al. (2001); Morón and Cozzolino (2002).
Zn	0.44-0.95	1.4-299	1.07-3.80	B	Malley and Williams (1997); Kooistra et al. (2001); Cohen et al. (2005); Viscarra Rossel et al. (2006).
Al	0.61-0.68	0.88-506.7	0.5-1.97	D	Siebielec et al. (2004); Cohen et al. (2005).

[a] Values of R^2, RMSEP and RPD do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

[b] Classification of accuracy into A, B, C, D and E was based on maximum number of publications confirming an accuracy category for a soil property. R^2: coefficient of determination, RMSEP: root mean square error of prediction, RPD: residual prediction deviation (SD/RMSEP), A: excellent (RPD > 3.0 and R^2 > 0.90; B: good (RPD = 2.5~3.0 and R^2 = 0.82~0.90), C: approximate quantitative prediction (RPD = 2.0~2.5 and R^2 = 0.66~0.81), D: distinguish between high and low (RPD = 1.5~2.0 and R^2 = 0.50~0.65) and E: not usable (RPD < 1.5 and R^2 < 0.5) (Chang et al., 2001).

From Table 2.2, it can be concluded that Fe, Cu and Zn can be measured with acceptable accuracy using the vis-NIR, which can be attributed to co-variation with other soil properties with direct spectral responses in NIR. Stenberg et al. (2010) explained that heavy metals can be detected because they can be complex with SOM, associated with hydroxides, sulphides, carbonates or oxides that are detectable in the vis–NIR, or adsorbed to clay minerals. However, Al is the worst property to be measured followed by Mn.

2.3.1.1.2. Non-mobile (in-situ) field vis-NIR spectroscopy

Although the application of vis-NIR spectroscopy has considerably reduced the labour and time for the analysis, soil sample preparation for laboratory analysis including drying, grinding and sieving is still tedious. For in-situ and on-line measurement with vis-NIR, calibration models developed from dried, ground and sieved samples cannot be utilised, since measurement is performed with fresh soil samples. As early as more than two decades ago, using an integrating cylinder and two narrow band interference filters, Barrett (2002) developed a spectrophotometric colour measurement for in-situ well drained sandy soils, reporting a moderately strong correlation. Fystro (2002) confirmed the ability of vis-NIR spectroscopy for measurement of OC, TN and their potential mineralisation in grassland soil samples, arriving at moderate accuracy ($R^2 > 0.7$ and RPD > 1.5). Udelhoven et al. (2003) evaluated the ability of NIR spectroscopy to estimate soil Fe, Mn, Ca, Mg and K and they found that only Ca and Mg ($R^2 = 0.67$ and 0.69, respectively) were predictable under in-situ conditions. Chang et al. (2005) attempted to predict TC, OC, TN, CEC, pH, texture, MC and potential mineralisable N and indicated that NIR was able to measure these soil attributes with reasonable accuracy using fresh soils ($R^2 > 0.74$).

Maleki et al. (2006) developed a calibration model of available P (P_{avl}) with acceptable prediction accuracy ($R^2 > 0.73$) based on fresh soil samples with the intention to be used for on-line variable rate P_2O_5 application system. Combining vis-NIR spectroscopy and laser induced breakdown spectroscopy (LIBS), Bricklemyer et al. (2005) reported moderate prediction accuracy ($R^2 = 0.70$) of TC and C_{inorg} under in-situ conditions. Meledenz-Pastor et al. (2008) identified optimal spectral bands to assess soil properties with vis-NIR radiometry in a semi-arid area and estimated SOM with worse accuracy ($R^2 = 0.73$, RPD = 1.92 and RMSEP = 0.52 %) than generally reported under laboratory condition. A summary of prediction performance of in-situ vis-NIR spectroscopy measurement of soil properties is reported in Table 2.3. A comparison between Table 2.1 and Table 2.3 reveals that laboratory vis-NIR methods (Table 2.1) provide better accuracy than in-situ field measurement, which can be attributed to the influence of MC and structure that were eliminated under laboratory conditions by drying, grinding and sieving.

2.3.1.1.3. Mobile (on-line) field vis-NIR sensors

Precision farming requires development of on-line sensors for real-time measurement of soil properties, because these sensors can lead to reducing labour and time cost of soil sampling and analysis. Compared to the non-mobile analysis, relatively less literature is available on mobile vis-NIR spectroscopy analysis of soil properties. A review on the current status of on-line vis-NIR measurement systems confirms that only three systems are available today (Christy, 2008; Mouazen et al., 2005; Shibusawa et al., 2001). The beginning of these systems

Table 2.3. *Summary of measurement accuracy of fundamental soil properties by in-situ visible and near infrared (vis-NIR) spectroscopy*

Soil properties	R^2 [a]	RMSEP	RPD	Accuracy	Key references
OC	0.51-0.96	0.29-1.40 (%)	1.30-4.95	B-C [b]	Fystro (2002); Udelhoven et al. (2003); Mouazen et al. (2010); Kuang et al. (2011).
TN	0.80-0.93	0.02-0.06 (%)	2.1-3.88	B	Chang et al. (2005); Fystro (2002); Mouazen et al. (2006a; 2006b).
pH	0.66-0.74	0.39-0.72	1.55-2.14	C	Chang et al. (2005); Mouazen et al. (2006a; 2006b; 2007).
Ca	0.77-0.86	1.63-1.68 (cmol kg^{-1})	2.10-2.19	C	Chang et al. (2005); Udelhoven et al. (2003); Mouazen et al. (2006a; 2006b).
CEC	0.78-0.89	1.77-3.57 (cmol kg^{-1})	2.31-2.33	C	Chang et al. (2005); Mouazen et al. (2006a; 2006b).
Clay	0.76-0.83	5.25-6.1 (%)	1.45-2.36	C	Chang et al. (2005); Waiser et al. (2007); Bricklemyer and Brown (2010).
Sand	0.49	12.44 (%)	0.87	E	Chang et al. (2005).
Silt	0.13	6.04 (%)	0.80	E	Chang et al. (2005).
MC	0.40-0.98	1.0-6.4 (%)	1.98-5.74	A	Ben-Dor et al. (2008); Mouazen et al. (2005); Slaughter et al. (2001).
Total P & P_{avl}	0.09-0.80	2.3-25 (mg $100g^{-1}$)	1.45-2.24	C	Bogrekci and Lee (2005a); Maleki et al. (2006); Mouazen et al. (2007).
Mg	0.49-0.84	0.30-0.30 (cmol kg^{-1})	1.39-1.56	D	Udelhoven et al. (2003); Chang et al. (2005); Mouazen et al. (2006a; 2006b).
K	0.33-0.87	0.21-3.90 (cmol kg^{-1})	1.21-2.80	D	Udelhoven et al. (2003); Zornaza et al. (2008); Mouazen et al. (2010); Wetterlind et al. (2010).
Na	0.13-0.77	0.025-0.129 (cmol kg^{-1})	1.29-1.98	E	Mouazen et al. (2006a; 2006b); Zornaza et al. (2008); Mouazen et al. (2010).

[a] Values of R^2, RMSEP and RPD do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

[b] Classification of accuracy into A, B, C, D and E was based on maximum number of publications confirming an accuracy category for a soil property. R^2: coefficient of determination, RMSEP: root mean square error of prediction, RPD: residual prediction deviation (SD/RMSEP), A: excellent (RPD > 3.0 and R^2 > 0.90; B: good (RPD = 2.5~3.0 and R^2 = 0.82~0.90), C: approximate quantitative prediction (RPD = 2.0~2.5 and R^2 = 0.66~0.81), D: distinguish between high and low (RPD = 1.5~2.0 and R^2 = 0.50~0.65) and E: not usable (RPD < 1.5 and R^2 < 0.5) (Chang et al., 2001).

dates back to 1991, when Shonk et al. (1991) developed a system to measure SOM and MC, which utilised a single wavelength (660 nm) of light (Table 2.4). Shibusawa (2001) developed an on-line vis-NIR (400 – 1700 nm) sensor to predict MC, pH, SOM and NO_3-N. Although this system is highly technically instrumented, it is rather expensive. Christy (2008) developed a prototype soil reflectance mapping unit equipped with a vis-NIR spectrophotometer, which is commercially available in the market. The sapphire glass of the optical probe makes direct contact with soil and stones. A simpler design to the one of Shibusawa (2001) without sapphire window optical configuration was developed by Mouazen et al. (2005). The system was successfully calibrated for MC, TN, TC, pH and available P in different soils in Belgium and northern France (Mouazen et al., 2005; Mouazen et al., 2009; Mouazen et al., 2007).

Comparing Tables 2.1 and 2.3 with Table 2.4 reveals that both the laboratory and in-situ non-mobile vis-NIR methods provide better accuracy than the on-line method, which is attributed to other factors influencing the latter methods. These factors include among others noise associated with tractor vibration, sensor-to-soil distance variation (Mouazen et al., 2009) stones and plant roots and difficulties of matching the position of soil samples collected for validation with corresponding spectra collected from the same position.

Table 2.4. *Summary of measurement accuracy of soil properties by on-line visible and near infrared (vis-NIR) spectroscopy*

Spectral range	nm	Results	Literatures
Single wavelength	660	SOM (r = 0.71)	Shonk et al. (1991).
vis-NIR spectrum	300-1700	MC, pH, SOM and NO_3-N (R^2 = 0.68, 0.61, 0.64 and 0.19, respectively)	Shibusawa et al. (2001).
NIR spectrum	1603-2598	SOM and MC (R^2 = 0.79 7 0.89, RPD = 2.17 & 2.86, respectively)	Hummel et al. (2001).
NIR spectrum	900-1700	MC, TC, TN, pH (R^2 = 0.82, 0.87, 0.86 and 0.72, respectively)	Christy (2008).
vis-NIR spectrum	300-1700	Similarity of OC, TC, MC, pH, P_{avl} and P_{ext} maps	Mouazen et al. (2007).
vis-NIR spectrum	350-2224	OC (SEP = 0.34) and clay content (RPD = 1.4, SEP = 6.94 %)	Bricklemyer and Brown (2010).

2.3.1.2. Mid infrared spectroscopy

When subjected to light, the fundamental molecular vibrations occur at frequencies in the mid infrared range (MIR) of 2500–25000 nm. However, overtones, combinations and overtones + combinations of these fundamental molecular vibrations occur in the NIR range (750–2500 nm). This is the reason why literature confirms superiority of MIR over vis-NIR spectroscopy for the measurement of soil properties, particularly, when dried and ground soil samples are used. Among different MIR spectroscopy techniques, the MIR diffuse reflectance and infrared attenuated total reflectance spectroscopy will be discussed in this paper. In external reflectance, the energy that penetrates one or more particles is reflected in all directions and this component is called diffuse reflectance. In the diffuse reflectance

(infrared) technique, commonly called DRIFT, the DRIFT cell reflects radiation to the powder/soil and collects the energy reflected back over a large angle. Diffusely scattered light can be collected directly from material in a sampling cup or, alternatively, from material collected by using an abrasive sampling pad. As sample preparation is easy with the DRIFT, it has been more commonly used for soil analysis. The attenuated total reflectance (ATR) spectroscopy utilises the phenomenon of total internal reflection. A beam of radiation entering a crystal will undergo total internal reflection when the angle of incidence at the interface between the sample and crystal is greater than the critical angle, where the latter is a function of the refractive indices of the two surfaces. The beam penetrates a fraction of wavelength beyond the reflecting surface and when a material that selectively absorbed radiation such as soil, is in close contact with the reflecting surface, the beam loses energy at the wavelength where the material absorbs. The resultant attenuated radiation is measured and plotted as a function of wavelength by the spectrometer and gives rise to the absorption spectral characteristics of the sample (Du and Zhou, 2009a).

2.3.1.2.1. Mid infrared spectroscopy for soil analyses

The start of using MIR spectroscopy for soil analysis dates back to 1991 (Nguyen et al., 1991). This has been extended for the analysis of several mineral species, OC and organic-N, minerals including carbonates and EC (Janik and Skjemstad, 1995; Janik et al., 1995). Since then, numerous researchers applied the MIR (Janik et al., 1998; Linker et al., 2004; Reeves III et al., 2001; Reeves et al., 1999).

Literature confirms that DRIFTS can outperform vis-NIR for the quantification of soil carbon (McCarty et al., 2002; McCarty and Reeves, 2006; Reeves III et al., 2001). Although very limited success has been reported for the measurement of soil nitrate with vis-NIR spectroscopy, MIR proved to be a successful technique due to the presence of nitrate vibration band around 1,350 cm^{-1} (Borenstein et al., 2006). By applying a straightforward chemometric approach, Linker et al. (2004) improved the determination accuracy and overcame some of the interferences associated with direct measurements in soil pastes. However, the correlation between soil nitrate concentration and the infrared absorption band is soil-dependent, due mostly to varying contents of carbonate (Jahn et al., 2006; Linker et al., 2004). MIR has the capacity of measuring soil microelements. Siebielec et al. (2004) found DRIFTS-MIR spectroscopy to be markedly outperforming NIR for the measurement of Fe, Cd, Cu, Ni and Zn, with R^2 of 0.97, 0.94, 0.80, 0.99 and 0.96, respectively.

Table 2.5 summarises the accuracy of soil properties measurement with MIR spectroscopy. The table proves that OC can be measured very successfully with MIR, with R^2 up to 0.99. Less accurate results can be achieved for TN or organic-N. Table 2.5 demonstrates that MIR can be used for the determination of soil texture, CEC, microelements with very good to excellent accuracy and with very good accuracy for soil pH. However, similar to the vis-NIR spectroscopy, the measurement of Na and K is unsuccessful, which can be attributed to the poor spectral signatures of these properties in both the vis-NIR and MIR regions. The accuracy for P_{avl} measurement with MIR tends to be less successful than OC, TN and texture. Surprisingly the accuracy for Mg and Ca measurement is found to be excellent and comparable to those for OC and TN.

Table 2.5. *Summary of accuracy of soil properties measured by mid-Infrared (MIR) spectroscopy*

Soil properties	R^2 [a]	RMSEP	Accuracy	Key references
OC	0.92-0.99	0.32-2.42 (%)	A [b]	McCarty et al. (2002); Madari et al. (2006); Bornemann et al. (2008); Reeves (2010).
TN	0.86-0.99	0.023 (%)	A	Janik and Skjemstad (1998); Du and Zhou (2009b); Minasny et al. (2009); Reeves III et al. (2001).
pH	0.56-0.90	0.16-0.45	B	Janik and Skjemstad (1998); Reeves III et al. (2001); Minasny et al. (2009); Viscarra Rossel et al. (2006).
Ca	0.38-0.96	18.7 (cmol kg^{-1})	A	Janik et al. (1995); Minasny et al. (2009); Viscarra Rossel et al. (2006).
CEC	0.34-0.92	4.6 (cmol kg^{-1})	B	Janik et al. (1995); Minasny et al. (2009); Viscarra Rossel et al. (2006).
Clay content	0.67-0.99	1.54-8 (%)	A	Minasny et al. (2009); Madari et al. (2006); Viscarra Rossel et al. (2006).
Sand content	0.74-0.97	2.47-7.7 (%)	A	Janik et al. (1995); Minasny et al. (2009); Madari et al. (2006); Viscarra Rossel et al. (2006).
Silt content	0.49-0.84	2.17-8.7 (%)	B	Cobo et al.(2010); Janik et al. (2009); Madari et al. (2006).
P_{avl}	0.07-0.94	6.2-29.3 (mg $100g^{-1}$)	C	Cobo et al. (2010); Janik et al. (2009); Du and Zhou (2009b); Reeves III et al. (2001); Viscarra Rossel et al. (2006).
Mg	0.76-0.94	18 (cmol kg^{-1})	A	Cobo et al. (2010); Janik and Skjemstad (1998); Minasny et al. (2009).
K	0.33-0.88	1.92-38.09 (mg kg^{-1})	E	Janik and Skjemstad (1998); Du and Zhou (2009b); Minasny et al. (2009); Cobo et al. (2010).
Na	0.31-0.72	0.6-1.1 (mg kg^{-1})	E	Janik and Skjemstad (1998); Janik et al. (2009); Minasny et al. (2009).

[a] Values R^2, RMSEP and RPD do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

[b] Classification of accuracy into A, B, C, D and E was based on maximum number of publications confirming an accuracy category for a soil property. R^2: coefficient of determination, RMSEP: root mean square error of prediction, RPD: residual prediction deviation (SD/RMSEP), A: excellent (RPD > 3.0 and R^2 > 0.90; B: good (RPD = 2.5~3.0 and R^2 = 0.82~0.90), C: approximate quantitative prediction (RPD = 2.0~2.5 and R^2 = 0.66~0.81), D: distinguish between high and low (RPD = 1.5~2.0 and R^2 = 0.50~0.65) and E: not usable (RPD < 1.5 and R^2 < 0.5) (Chang et al., 2001).

Due to the large effect of MC on MIR spectra, masking spectral features of other soil properties (Reeves, 2010), NIR spectroscopy provides better results under in-situ field

conditions. The sample preparation needed for MIR is another reason for hindering the field implementation of MIR for soil analysis. Furthermore, no report on using MIR for on-line measurement of soil properties has been published so far.

2.3.2. Conductivity, resistivity and permittivity based soil sensors

Within this class of sensors various principles are being used to measure soil properties directly or indirectly through an assessment of electrical conductivity, resistivity and permittivity. This class includes measurement of electrical resistivity (ER) or conductivity (EC), time domain reflectance (TDR), frequency domain reflectance (FDR), ground penetrating radar (GPR) and electromagnetic induction (EMI).

2.3.2.1. Electromagnetic induction (EMI)

The EMI sensors are based on Faraday's law used in physics. EMI is a contactless non-invasive method. De Jong et al. (1979) reported that the use of EMI for mapping sub-surface geology by injecting electrical current into the soil started in the beginning of 20th century. In agriculture, the EMI technique was first introduced in the late 1970's for salinity appraisal (Corwin and Rhoades, 1982; de Jong et al., 1979; Rhoades and Corwin, 1981; Williams and Baker, 1982). Nowadays, this technique is mature and has become a commonly used practice for quick characterisation of in-field variability.

The EMI device is composed of a transmitter coil and a receiver coil installed on both ends of a nonconductive bar. The principle of EMI devices is described in detail by McNeill (1980b). In short, the transmitter coil at or above the ground surface is energised with an alternating current, creating a primary, time-varying magnetic field in the soil. This magnetic field induces small eddy currents in the soil, while the soil matrix produces a weak secondary magnetic field. The receiver coil responds to both the primary and weak secondary magnetic fields. The secondary magnetic field is, in general, a complicated function of the inter-coil spacing, operating frequency and ground conductivity. As soil conductivity is not homogeneous, the EMI device measures electrical conductivity of the total volume of soil contributing to the signal. Soil conductivity is, therefore, called apparent or bulk soil electrical conductivity. Operating at low induction numbers, the ratio between the primary magnetic field and secondary magnetic field is a linear function of bulk or apparent soil electrical conductivity (ECa).

The magnitude and phase of the secondary magnetic field measured by receiver coil differ from the primary magnetic field due to soil properties, spacing between transmitter and receiver and instrument orientation i.e. horizontal or vertical dipole mode (Hendrickx and Kachanoski, 2002). Also, the exploration depth of the EMI signal depends on the separation between transmitter and receiver coils, the orientation of the instrument and operating frequency (McNeill, 1980b). Increasing the operating frequency will decrease the exploration depth of the measurements.

Soil ECa measured by EMI devices is affected by conductors buried in the soil as well as the physical and chemical properties of the soil matrix. The soil conductors, other than metallic objects, are dissolved electrolytes in the soil water, conductive minerals formed by rocks,

clays and clay minerals (McNeill, 1980a). In the absence of metal objects, the soil conductivity is primarily electrolytic since most soil and rock minerals are poor electrical conductors. The conductivity of all these electrolytes is proportional to the total number of ions in solutions, their charges and velocities. In addition to electrolytes, several soil physical properties, including porosity (shape, sizes and number of pores and inter pore distances), moisture filled macro pores and pore water temperature greatly affect soil conductivity. More details about these factors can be found in McNeill (1980a) and Friedman (2005). As EMI is affected by all these factors, this induces problems when separation of individual effects is desired. Therefore, the majority of applications of EMI in precision agriculture are aimed at mapping variability and to delineate management zones that can be used for site specific land management (Corwin and Lesch, 2003; Rhoades et al., 1999a).

Soil ECa can either be determined manually in-situ in the field or with an on-line setup. Initially, soil ECa was determined with EMI meters manually. In manual soil ECa measurement, the sensor is placed on the ground on selected points following any measurement system for example, regular grids (Rhoades and Corwin, 1981; Rhoades et al., 1989a; Williams and Baker, 1982). Manual methods are suitable for point measurements. In the later research, for having complete ECa variations in a field, real-time conductivity sensing was introduced. For real-time or on-line ECa measurement, the EMI sensors are mounted on a mobile system (all-terrain vehicle or quad bike) and soil ECa can be recorded in a data logger while also registering GPS coordinates of each point (Cannon et al., 1994; Kitchen et al., 1996; Sudduth et al., 2003; Sudduth et al., 2005). As soil ECa can only be measured from bulk soil with large volumes, this technique cannot be used in a laboratory.

EMI based ECa surveys have widely been used in agriculture to measure various soil physico-chemical properties (Lesch et al., 2005) and numerous authors claim to quantitatively map different soil properties such as salinity (e.g. Hendrickx et al., 1992), clay content (e.g. Williams and Hoey, 1987) and MC (e.g. Kachanoski et al., 1988; Sheets and Hendrickx, 1995) with ECa measured by EMI devices. The EMI applications are most suitable in the areas where subsurface properties are reasonably homogeneous and the effect of one soil property dominates over the others.

Numerous authors predicted soil salinity from ECa survey data with manual measurement (e.g. Hendrickx et al., 1992; Rhoades et al., 1989b; Williams and Baker, 1982). Other soil properties that have also been successfully mapped using ECa data include clay content (e.g. Williams and Hoey, 1987), depth to clay layers (e.g. Doolittle et al., 1994) and MC (e.g. Kachanoski et al., 1988; Sheets and Hendrickx, 1995). Above ground ECa was also reported to relate to near-surface soil properties other than salinity in later research (Abdu et al., 2007; Hossain et al., 2010; Jung et al., 2005). The most relevant literature is reviewed in Table 2.6. A number of EMI sensors is available in the global market for ECa measurement (e.g. EM31, EM34, EM38, GEM, etc.), however, reviewing literature on all those sensors is beyond the scope of this paper. We, therefore, review the most relevant literature found using the most frequently used EMI device, the EM38.

Table 2.6. *Accuracy of soil properties related directly or indirectly with electrical conductivity (ECa) measured by an EM38*

Soil property	Platform	R^2 [a]	Key references
Salinity or Na^+	In-situ	0.50- 0.98	McNeill (1992); Rhoades et al. (1999a); Herrero et al. (2003); McLeod et al. (2010).
	On-line	0.40-0.70	Triantafilis et al. (2002); Corwin and Lesch (2003); Arriola-Morales et al. (2009).
Water content	In-situ	0.37-0.99	Kachanoski et al. (1988); Hanson and Kaita (1997); Reedy and Scanlon (2003); Hossain et al. (2010).
	On-line	0.23-0.70	Sudduth et al. (2005); Hezarjaribi and Sourell (2007).
Texture/topsoil depth	In-situ	0.20-0.90	Williams and Hoey (1987); Domsch and Giebel (2004); Jung et al. (2005); Saey et al. (2009).
	On-line	0.47-0.94	Kitchen et al. (1996); Sudduth et al. (2005).
CEC, NO_3^-, SOM, pH, Ca^{2+}, Mg^{2+}, etc.	In-situ	0.18-0.76	McBride et al. (1990); Corwin and Lesch (2005b); Hedley et al. (2004); Bronson et al. (2005).
	On-line	0.22-0.81	Triantafilis et al. (2002); Sudduth et al. (2001; 2003; 2005).

[a] R^2 values do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

2.3.2.2. Electrical resistivity (ER)

Electrical resistivity (ER) sensing is a contact-based soil sensing technique which introduces an electrical current into the soil through the contact electrodes and the difference in current flow potential is measured at potential electrodes that are placed in the vicinity of the current flow. The ER technique requires good contact between the soil and four electrodes. In stony or dry soil, there may be chance of improper contact between the soil and electrodes. This is a drawback of the technique, which might give less reliable measurements as compared to the EMI technique. ER methods introduce an electrical current into the soil through current electrodes at the soil surface and the difference in current flow potential is measured at potential electrodes that are placed in the vicinity of the current flow. This method measures bulk soil resistivity and the reciprocal of which is ECa. Three parallel path lines for current flow in soil contributing to soil ECa are: (1) continuous liquid, (2) continuous solid and (3) solid-liquid series (Rhoades et al., 1999b). The four electrode configuration is referred to as a Wenner array provided these electrodes are equally spaced and mounted on a frame in a straight line. The outer two electrodes are current transmission electrodes while the inner two electrodes are receiving or potential electrodes. The depth of penetration of the electrical current and the volume of measurement increase as the inter-electrode spacing increases. The electrode method, therefore, offers an option to sense soil resistivity of desired depth by changing the inter-electrode distance. More than four electrodes can also be accommodated with different Wenner array configurations as discussed by Telford et al. (1990) and Burger (1992).

Soil ECa sensors are among the technologies that have helped to bring precision agriculture from a concept to a potential tool for addressing the issue of agricultural sustainability

(Corwin and Lesch, 2003). Initially, the measurement of ER was done with four electrodes that were widely used in a variety of applications including geophysical imaging. The ER methods were developed for evaluation of ground resistivity in 1920's by Conrad Schlumberger in France and Frank Wenner in the United States (Corwin and Lesch, 2003). ER and electrical resistivity tomography (ERT), which is an extension of ER, both are geophysical techniques that measure subsurface electrical structures using conduction current. An ER sensor images one dimensional (1-D) i.e. vertical resistivity sounding while ERT is capable to carry out 2-D (horizontal profiling) and 3-D (combined sounding-profiling) imaging of ground surface. In ERT, from a series of electrodes, low frequency electrical current is injected into the subsurface and the resulting potential distribution is measured. ERT was proposed by Webster et al. (1978) as a medical imaging modality and by Lytle et al. (1978) as a geophysical imaging tool and now it has been widely used for hydrogeophysical investigation (Binley and Kemna, 2005). Different types of electrode arrays are available based on type of sounding, for example, Wenner, Schlumberger, equatorial, dipole-dipole, bipole-dipole, etc. In soil science and hydrological applications, 2-D subsurface imaging is mostly done using ground penetrating radar as discussed later. The ERT is not common in soil science and precision agricultural applications due to the fact that 2-D and 3-D imaging models demand more data intensive surveys and data handling and practical computer interpretation is also complicated (Loke, 1999). Such surveys are usually carried out using a large number of electrodes, 25 or more, connected to a multicore cable. Although nowadays with the advent of fast computers and data handling tools, techniques to carry out 2-D resistivity surveys are fairly well developed, yet little research is exploited in agriculture related applications. For agricultural based applications only vertical resistivity sounding is widely used. Therefore, we limit this review to only ER methods used for soil property mapping.

Electrical conduction through soil is due to the presence of free salts in the soil solution and exchangeable ion at the surfaces of solid particles. A number of factors affect resistivity or ECa measured by ER techniques. The resistivity of soil particles depends on the parent material. Sedimentary rocks, which usually are more porous and have higher water content, normally have lower resistivity values. Similarly, wet soils and clayey soils have lower resistivity than dry and sandy soils, respectively. The most influencing factors are clay and clay minerals, water content and salts content (McNeill, 1980a). Furthermore, ER is known to be sensitive to other physical factors such as soil solution (Besson et al., 2008; Friedman, 2005), soil mineralogy, pore-water conductivity and percentage of clay (Samouëlian et al., 2005). The detailed factors affecting ER can be found in Samouëlian et al. (2005).

ER measurement was first introduced to soil science in the 1970's to determine soil salinity due to the fact that soil solution extraction in the laboratory is time consuming and cost intensive and also due to high local-scale variability associated with small volume soil core samples. Rhoades (1970) was the first who demonstrated that soil salinity could be assessed in the field from bulk soil EC without recourse to soil sampling and analysis with the help of equally spaced four electrodes. After this many researchers focused on in-situ soil salinity measurement using four electrodes ER/ECa surveys (e.g. Cameron et al., 1981; Rhoades, 1976; Rhoades, 1979; Rhoades et al., 1990). In another study, Halvorson and Rhoades (1976) acquired ECa data using four electrode systems and created maps of soil salinity variations in a field. For in-situ salinity measurements the four-electrode methods (Wenner configuration)

can be applied on the soil surface as well as in boreholes (Halvorson and Rhoades, 1976; Rhoades, 1979). After salinity characterisation, the ER method was extended to measure MC (e.g. Freeland, 1989), texture (e.g. Banton et al., 1997), CEC (e.g. McBride et al., 1990) and SOM (e.g. Banton et al., 1997). With the course of time the ER was extended from in-situ to on-line measurement of ECa using electrode/coulter based sensors for various applications. A tractor mounted version of the electrode-based sensor was used for mobile and geo-referenced measurements of ECa (Rhoades, 1993). Lund et al. (2000; 1999) also used tractor mounted on-line ECa measurement and related this with several soil properties. Other soil properties measured with on-line ECa using resistivity systems include MC (e.g. Hartsock et al., 2000), texture (e.g. Sudduth et al., 2003; Sudduth et al., 2005), salinity (e.g. Corwin and Hendrickx, 2002), CEC (e.g. Officer et al., 2004) and soil variability (e.g. Shaner et al., 2008). Key references for using ER methods to characterise soil properties are given in Table 2.7.

Table 2.7. *Soil properties measured by contact type electrical resistivity (ER/ECa) sensors*

Soil property	Platform	R^2 [a]	Key references
Salinity or Na^+	In-situ	0.66-0.99	Rhoades (1979); Cameron et al. (1981); McBride et al. (1990); Rhoades et al. (1990).
	On-line	0.35-0.90	Corwin and Hendrickx (2002); Farahani and Buchleiter (2004).
Water content	On-line	0.40-0.85	Hartsock et al. (2000); Johnson et al. (2001); Farahani et al. (2005); Sudduth et al. (2005).
Texture/topsoil depth	In-situ	0.20-0.64	Rhoades et al. (1990); Banton et al. (1997).
	On-line	0.40-0.92	Kitchen et al. (2003); Bronson et al. (2005); Sudduth et al. (2005); Moral et al. (2010).
CEC, NO_3^-, SOM, pH, Ca^{2+}, Mg^{2+}, etc.	In-situ	0.32-0.80	McBride et al. (1990); Banton et al. (1997).
	On-line	0.40-0.85	Officer et al. (2004); Sudduth et al. (2005); Jabro et al. (2006); Shaner et al. (2008).

[a] R^2 Values do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

2.3.2.3. Ground penetrating radar

Ground penetrating radar (GPR) is basically a geophysical technique which is particularly appropriate to image the soil in two or three dimensions with a high spatial resolution up to a depth of several meters. In the last decade, the GPR has extensively been used in various disciplines including agriculture, where GPR imaging was used to determine soil properties and their spatial distribution. Much progress in the technology itself has been made in this period by improving the dynamic range of systems and efficiency of the antennas, speed of acquisition, real-time image acquisition and visualisation and basic processing of radar images (Lambot et al., 2009a).

The working principle of GPR is similar to reflection seismic and sonar techniques (Davis and Annan, 1989). Electromagnetic (EM) waves are transmitted towards the soil and from the reflections of this wave, properties of the soil can be extracted. The theoretical aspects of radar components and their working principles can be found in detail in Daniels (2007) and

Jol (2009). GPR systems work in a frequency range of 10-5000 MHz (e.g. VHF-UHF). The main characteristics of a GPR system are its operating frequency (centre frequency), resolution and depth of penetration. GPR resolution is the ability of the system to distinguish two signals that are close to each other in time. Usually, the resolution of a GPR increases with increasing operating frequency (Davis and Annan, 1989; Huisman et al., 2003). As the penetration depth reduces with increasing frequency, the choice of an operating frequency is always a trade-off between resolution and penetration depth, as higher frequencies permit higher resolution but lower penetration depth (Davis and Annan, 1989). The depth range of GPR is also strongly influenced by the electrical conductivity of the soil.

Propagation of the EM waves into the soil is mainly governed by soil dielectric permittivity (ε) (determining wave velocity), electrical conductivity (σ) (determining wave attenuation), magnetic permeability (μ) (determining wave velocity and affecting wave attenuation) and their spatial distribution (Lambot et al., 2009a; Lambot et al., 2007). Reflection of the EM wave is caused by soil layers having a different permittivity. Both the reflection and attenuation of the EM wave offer the opportunity to assess properties of the soil.

The more electrically conductive a material is, the more the EM wave will be attenuated. Metallic objects buried in the soil can change the electrical conductivity drastically. Soils, rocks or sediments, which are normally dielectric (insulators), permit the penetration of radar waves without attenuation. When the EC of soils or rocks increases, the EM energy will be dissipated. Soil salinity and soil water content are the two factors that strongly influence soil conductivity (Daniels et al., 1995). Also other factors affect the EC of the ground, such as porosity, clay types, clay mineralogy, CEC and dissolved ions in the soil water present in macro pores (McNeill, 1980b). Sulphates, carbonate minerals, iron, salts of all sorts and charged clay particles create a highly conductive soil and readily attenuate radar energy at shallow depth (Ben-Dor et al., 2009). Magnetic permeability is another factor which affects the GPR ability to penetrate in the soil. Soils and rocks containing magnetic minerals such as iron oxide have a high magnetic permeability and therefore attenuate radar waves in transmission (Ben-Dor et al., 2009).

Similar as with EMI and ER measurements, it seems possible to decipher the influence of a single soil characteristic by means of GPR. However, when many factors interact and contribute to soil EC, then it always remains difficult to estimate these characteristics with radar waves.

GPR is a very promising tool for imaging primarily the subsurface features (Annan, 2002). The GPR appeared in soil property mapping to determine soil MC (e.g. Chanzy et al., 1996; Van Overmeeren et al., 1997; Weiler et al., 1998). The application of a GPR system for MC as well as measurements of other soil properties was mostly implemented as in-situ sensing (e.g. Lambot et al., 2008; Minet et al., 2009; Müller et al., 2009; Serbin and Or, 2004). Some authors also attempted to measure soil MC on-line (e.g. Jadoon et al., 2010), however, there is not much published work available. Other applications of GPR include the measurement of soil texture (e.g. Boll et al., 1996; Gerber et al., 2010; Truman et al., 1988; West et al., 2003), salinity (e.g. Al Hagrey and Müller, 2000), soil compaction (e.g. Petersen et al., 2005) and water table (e.g. Smith et al., 1992), to identify soil stratigraphy (e.g. Davis and Annan, 1989), to monitor subsurface contaminants (e.g. Kim et al., 2000), to find the depth of soil horizons and

thickness (e.g. Collins and Doolittle, 1987), to delineate hard pans (e.g. Raper et al., 1990), to infer soil colour or OC content (e.g. Doolittle, 1982), to identify subsurface hydraulic parameters (e.g. Lambot et al., 2009b) and to characterise the depths of organic soil materials (e.g. Shih and Doolittle, 1984). Some key references of GPR applications are given in Table 2.8.

Table 2.8. *Soil properties measured in-situ with ground penetrating radar (GPR) techniques*

Soil property	R^2 [a]	Key references
Water content	0.57-0.95	Davis and Annan (2002); Grote et al. (2003); Huisman et al. (2003); Lambot et al. (2008).
Texture/topsoil depth	0.55-0.85	Boll et al. (1996); West et al. (2003); Petersen et al. (2005); Gerber et al. (2010).
Salinity	0.60-0.85	Shih et al. (1985); Al Hagrey and Müller (2000); Tsoflias and Becker (2008).
Compaction	0.45-0.70	Petersen et al. (2005); Freeland et al. (2008).

[a] R^2 values do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

2.3.2.4. Permittivity based sensors

Permittivity based soil sensors measure changes in dielectric properties of soils. The sensors in this category measure soil dielectric constant or permittivity (ε) by transmitting an electromagnetic (EM) wave into the soil matrix. These sensors are categorised as time domain reflectometry or reflectometers (TDR) and frequency domain reflectometry or reflectometers (FDR). Dielectric sensors are mostly used for determining MC. Popular techniques such as TDR and capacitance, to measure soil MC depend on dielectric constant of soils. Dielectric constant of water (~80) is greater than that of soil matrix materials (~4) or of air (~1). Some TDRs and FDRs can also measure soil ECa based on the dielectric constant of soil. Laboratory methods of measuring soil MC are time consuming and expensive. Dielectric sensors either based on the FDR or TDR principle, can be a cost effective alternative to laboratory methods. Table 2.9 lists some key references. In the following sections both FDR and TDR are described in more detail.

2.3.2.4.1. FDR sensors

The FDR probe incorporates an oscillator circuit. The oscillation frequency is determined by an annular electrode, or fringe effect capacitor, the value of which depends on the dielectric properties of the soil in which it is inserted. The oscillation frequency decreases with the increase in soil MC (Whalley et al., 1992). The probe measures the frequency and by using calibration data, one can determine the volumetric MC (Dean et al., 1987; Wobschall, 1978). The MC has a linear relationship with fringe-capacitance for MC >10 %. MC from 5 to 45 % has a linear relationship with the log of fringe-capacitance. As the electrodes should generate an adequate 'fringing' field, its size and construction requires attention. For proper results, the operation frequency should exceed 30 MHz (Thomas, 1966).

Since the first use of the FDR sensor, many authors have investigated its abilities for sensing MC. The sensor is easy to calibrate and performs very well. Accuracy was very high with R^2

exceeding 0.90 (Table 2.9), under in-situ and on-line measurement conditions. The EC-5 probe (Decagon Devices, Pullman, WA, USA) was recommended by Parsons and Bandaranayake (2009) for in-situ measurement of soil MC as the probe produced good calibration results ($R^2 = 0.95$) during laboratory measurements.

An FDR probe sensor can be integrated into soil cutting tool and horizontal or vertical penetration cone to perform on-line measurement of soil MC. Whalley et al. (1992) carried out on-line measurement using a tine-shaped sensor with two capacitor electrodes separated by an insulator. Results provided good calibration but were affected by soil dry bulk density (BD). Sun et al. (2006) used the capacitance principle to measure soil MC at the same time as measuring penetration resistance (PR). Two metallic strips were separated by three strips of insulation and both metallic strips act as two electrodes of the fringe-capacitance sensor. They achieved very good results during laboratory calibration ($R^2 = 0.98$) and in the field ($R^2 = 0.99$). Another commercial alternative is the Theta Probe (Gaskin and Miller, 1996) that has been developed jointly by the Macaulay Land Use Research Institute, Aberdeen and Delta-T Devices, Cambridge. The Theta Probe has proven to be useful instrument to measure volumetric MC (Kaleita et al., 2005; Scott et al., 2005; Walker and Houser, 2002).

2.3.2.4.2. TDR sensors

The TDR sensors send an EM pulse into an electrode inserted in the soil. The change in permittivity at the transient between electrode and soil will cause a reflection with the delay and intensity depending on the properties of the soil. TDR is described in more detail by Wraith (2002), who provides an excellent overview of the principles, equipment, procedures, range and precision of measurement and calibration.

TDR calibration is vital to achieve maximum accuracy and therefore probe impedance relationship with soil electrical conductivity has to be established under laboratory conditions before TDR can be used on field (Heimovaara, 1993). The traditional method of calibrating TDR involves adding of MC to the soil sample and mixing thoroughly to allow reaching equilibrium. The soil is packed to pre-specified BD and the TDR probe is inserted. TDR waveforms are then collected. This process is repeated until enough points are measured for a calibration graph. TDR is established as a non-destructive method of measuring soil MC (Dalton and Van Genuchten, 1986; Davis and Annan, 1977; Topp et al., 1980; Wang and Schmugge, 1980; Wobschall, 1977). This technique offers high accuracy and flexibility and hence is a preferred technique for in-situ measurement of MC and electrical conductivity (Robinson et al., 2003; Thomsen et al., 2007). Young et al. (1997) carried out laboratory experiments to calibrate the TDR probe for various soils and found that the probe can measure volumetric MC with high accuracies ($R^2 > 0.99$). Stangl et al. (2009) suggested that for TDR based sensors, sensor response depends strongly on site specific soil properties and that the general manufacturer's calibration provided error in readings. It was recommended that site-specific calibration should be carried out to avoid error in data samples. Robinson et al. (2003) recommended Heimovaara (1993) method of calibrating a TDR probe. Literature confirms good results for the measurement of the volumetric MC using TDR, with $R^2 > 0.80$, which is smaller than results obtained with capacitance sensors (Table 2.9).

For large number of readings, a handheld TDR probe is not helpful and automated measurement system is recommended as a more economical method. Probes of 0.50 to 0.70 m in length are recommended. Probes longer than 0.70 m require a more complex design including a slide guide to prevent the probes from bending and keep them parallel during insertion. Intensive measurements are required to quantify the spatial variation of soil MC and texture measurement (Thomsen et al., 2007). A complete TDR system built by Thomsen et al. (2007) was capable of measuring soil MC on dry or stony soils. The system consisted of a tractor mounted frame with hydraulic sub-system for fast insertion and retrieval of TDR probes. TDR probes were vibrated using a hydraulic hammer while inserting in to soil. This allowed probes to penetrate dense and strong stony soils easily, a process which otherwise would have resulted in damage to the probes. This device can take one full measurement in under 1 minute for measuring points less than 25 m apart. The authors concluded that to increase the number of repetitions to double or triple observations per sampling point in a regular grid, grid needs to smaller than 25 m just so that spatial variability of field MC can be obtained at a good resolution.

Table 2.9. *Soil moisture content measured in laboratory and in-situ using frequency domain reflectometry (FDR) and time domain reflectometry (TDR)*

Sensor/Method	Platform	R^2 [a]	Key references
TDR	Laboratory	0.80 – 0.99	Dalton et al. (1984); Heimovaara (1993); Young et al. (1997); Stangl et al. (2009).
	In-situ	0.84 – 0.99	Topp and Davis (1985); Dasberg and Dalton (1985); Dalton and Van Genuchten (1986); Wu et al. (1997).
	On-line	0.90 – 0.95	Thomsen et al. (2007).
FDR	Laboratory	0.90 – 0.99	Wobschall (1977); Gaskin and Miller (1996); Robinson et al. (1999); Parsons and Bandaranayake (2009).
	In-situ	0.90 – 0.98	Thomas (1966); Dean et al. (1987); Walker and Houser (2002); Kaleita et al. (2005).
	On-line	0.90 – 0.98	Whalley et al. (1992); Sun et al. (2006).

[a] R^2 values do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

2.3.3. Passive radiometric sensing

Radiation based soil sensors detect radiations originating from earth's surface. It is well known fact that all objects above the temperature of absolute zero (-273.15° Celsius) radiate EM waves to their surrounding environment. These radiations are of different types identified on the basis of wavelength, for example, ultraviolet, visible, infrared, radio waves, gamma rays, etc. Though passive microwave sensing could be used on ground based mobile platforms (e.g. Chukhlantsev et al., 1989; Macelloni et al., 1998), this approach has received most attention in the past decades in the context of airborne and satellite based remote sensing (Mulder et al., 2011). Thermography is another example that has not received much attention in recent literature. Therefore this review will focus on a relatively new sensing principle based on the detection of gamma rays emitted by the soil.

2.3.3.1. Gamma-ray spectrometers

Gamma-ray spectrometry or radiometrics has evolved over several decades and is widely used in mineral exploration and environmental and geological mapping (Dickson and Scott, 1997). Gamma-ray spectrometry or radiometric technology is a non-invasive, non-destructive and a passive technique. It is a relatively new soil sensing technique that measures gamma radiation emitted from the natural decay of radioactive isotopes that are present in all soils (Cook et al., 1996). Many naturally occurring elements have radioactive isotopes, but only potassium (K), uranium (U) and thorium (Th) decay series have radioisotopes and associated daughter products that produce gamma rays of sufficient energy and intensity to be measured by gamma-ray spectrometry. Individual radionuclides emit gamma rays of specific energies that are characteristic for an element and an isotope (IAEA, 2003).

The presence of radioisotopes such as K, Th and U in soils and rocks associates with certain constituents. Gamma rays emitted from the surface will relate to the mineralogy and geochemistry of the bedrock and weathered materials, for example, soils, saprolite, alluvial and colluvial sediments. Understanding the bedrock and regolith responses has proved invaluable not only for mapping regolith materials but also for understanding geomorphic processes (Wilford, 2002; Wilford et al., 1997). Wilford and Minty (2006) explained briefly how these radioisotopes come from rock minerals. For instance, the concentration of K, Th and U contents in soils and rocks generally increases with increasing silica content. The concentration of K decreases with increased weathering. This is because K is soluble under most weathering environments and tends to be leached from a soil/regolith profile. On exceptional occasions, the K is incorporated into potassic clays such as illite. Otherwise, it is either absorbed onto clays such as montmorillonite and kaolinite, or associated with either large K-feldspar phenocrysts or mica that take time to weather. In contrast, U and Th are associated with more stable weathering products in soil profiles. U and Th released during weathering are readily absorbed onto clay minerals, Fe, Al oxyhydroxides and organic matter in soils. In addition, U and Th also reside in resistate minerals that persist for a long time in the soil. It is therefore not uncommon for relative concentrations of U and Th to increase in highly weathered soils, as other more soluble minerals are lost in solution (Wilford and Minty, 2006). Detailed information about the geological and geochemical laws governing the behaviour of radioisotopes in radiometrics can be found in Dickson and Scott (1997) and Hyvönen et al. (2005).

Minty (1997) gave a good summary of the fundamentals of airborne gamma-ray spectrometry, whereas IAEA (2003) presented guidelines for radioelements mapping using gamma-ray spectrometry. Further, information about theory and method, surveying technique, data processing and interpretation in airborne gamma-ray spectrometry can be found in Minty (1997), Wilford et al. (1997) and Zhang et al. (1998). Gamma-ray spectra are typically recorded at a frequency of up to 1 Hz. The gamma spectrometers can be used by mounting on an aircraft or on ground vehicles to scan the fields. Portable, hand-held gamma-ray spectrometers are widely used in mineral exploration and environmental studies. Now spectrometers are also available to be used in laboratory and sea-bottom surveying purposes. The spectrometers detect total gamma counts as well as individual radionuclide counts. Total counts are used to monitor the gross level of the gamma radiation and to

detect the anomalous sources, whereas the individual counts give the intensity and energy of radiation of individual radioactive element in the soil matrix.

Fifty per cent of the observed gamma rays originate from the top 0.10 m of dry soil and 90 % from the top 0.30 m (Taylor et al., 2002). The environmental factors that may influence the gamma-ray measurements are air temperature, pressure and movement in lower atmosphere, precipitation, dense vegetation, soil MC, background radiation and non-radioactive overburden. Generally, an increase in soil MC to a certain extent may decrease the radiation flux to the same extent (Grasty, 1997). High soil MC with increased BD can result in decreased gamma radiation flux, especially in K and Th decay series (Carroll, 1981; Carroll, 1982; Grasty, 1997; Lundien, 1967). Maximum gamma radiation can be obtained from the soil matrix in summer when temperature is high. The dense vegetation not only attenuates the gamma radiation but in addition it acts as a source of gamma radiation itself.

Commercially available gamma spectrometers are manufactured based on the utility and the purpose and are available in various types, models or dimensions. The spectrometers use different types of detectors or scintillation crystals such as BGO, NaI(Tl), CsI(Tl), HP(Ge), etc. Some of the spectrometers are used for soil property mapping such as clay content of top 30 cm soil, which can be imaged using thorium and potassium counts.

The recorded data with gamma-ray sensors require substantial processing before making accurate estimates of the ground concentrations of K, U and Th radioisotopes (Minty, 2001; Wilford and Minty, 2006). Statistical noise is usually first removed from the raw multichannel gamma-ray spectra using a statistical noise-reduction technique such as noise adjusted singular value decomposition (NASVD) (Dickson and Taylor, 1998; Hovgaard, 1997; Hovgaard and Grasty, 1997; Minty and McFadden, 1998; Tammenmaa et al., 1976) or maximum noise fraction (MNF) (Dickson and Taylor, 2000; Dickson, 2004; Green et al., 1988). Principal component analysis methods are used to extract the dominant spectral shapes from the survey data. More information about the two methods can be found in Dickson and Taylor (1998).

In soil science applications, portable gamma radiometers gained interest during the last decade for mapping individual soil properties (Pracilio et al., 2005; Pracilio et al., 2006; Wong and Harper, 1999). These ground based gamma spectrometers were used to estimate soil texture (Mahmood et al., 2011; Roberts, 2003; Taylor et al., 2002; Viscarra Rossel et al., 2007), plant available K (Wong and Harper, 1999) and other minerals (Van Egmond et al., 2010; Viscarra Rossel et al., 2007). To incorporate the other useful information together with region of interest (ROI), a full spectrum analysis is recommended and being used for minimal loss of information from gamma spectra (Hendriks et al., 2001; Viscarra Rossel et al., 2007). The ground-based gamma spectrometers are used as an on-line system to measure gamma counts. There are some small handheld gamma spectrometers to be used in-situ as well as in the laboratory. However, there is not any published literature on the accuracy of such type of mini spectrometers for measuring soil properties. Therefore, the reviewed literature (Table 2.10) enlists the most relevant studies for characterising soil properties from proximal, ground-based platform only.

Table 2.10. *Soil properties measured with on-line proximal gamma ray spectrometry*

Soil property	R^2 [a]	Key references
Soil texture, topsoil depth, parent materials	0.42-0.90	Wong and Harper (1999); Taylor et al. (2002); Viscarra Rossel et al. (2007).
Organic carbon/SOM	0.40-0.90	Wong and Harper (1999).
Soil pH	0.20-0.76	Viscarra Rossel et al. (2007).
Available K and P	0.50-0.90	Wong and Harper (1999).
Fe, N, Mg, Cd, etc.	< 0.90	Viscarra Rossel et al. (2007); Van Egmond et al. (2010).

[a] R^2 values do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

2.3.4. Soil strength sensors

Soil strength changes with time under influence of climate, soil management and plant growth (Koolen and Kuipers, 1983). Soil mechanical properties under external loads of tillage tools and agricultural machinery are influenced by several factors including BD, MC, SOM and soil texture type (Mouazen et al., 2002). Methods for the measurement of soil strength include laboratory, in-situ and on-line measurement techniques.

Soil shear strength is soil resistance to deformation by applied external shear forces, for example, during soil cutting process with different tillage tools. Shear failure occurs when shear forces exceed a maximum limit called yield strength. However, shear failure can also occur under compression load, for example, under tyres, which makes soil as bulk material behaves differently than metals under compression load (McKyes, 1989). The soil shear strength is represented as sum of soil cohesion (C) and internal frictional angle (φ). Cohesion is, contrary to friction, independent of loading on soil particles. By determining the maximum shear stress at corresponding normal stresses, one can determine cohesion and internal friction angle. Measurement methods of soil shear strength are explained below.

2.3.4.1. Laboratory measurement methods of shear strength

2.3.4.1.1. Direct shear box

When carrying out a test, each sample is placed within two square rings. During each test, a normal pressure is applied to the upper part of the soil, while the bottom part is moved horizontally. The relative displacement versus shear force is recorded and the soil shear strength properties are estimated based on the Coulomb's criterion.

2.3.4.1.2. Triaxial compression test

The triaxial compression apparatus allows remoulded or undisturbed soil samples to be tested. Remoulded soil specimens are prepared in cylindrical shape after controlling the BD and MC. The soil cylinders are then surrounded by a rubber membrane and confined by water pressure in a water-filled load cell. During the tests, an axial principal stress is generated on the top of the cylinder. Differences between lateral and axial principal stresses

generate shear stresses on various planes in the soil cylinder. The cylindrical sample will start to deform after a certain axial displacement continuing with changes in volume and shape. Using a Mohr's Circle diagram C and φ can be determined (Koolen and Kuipers, 1983).

2.3.4.2. In-situ measurement methods

2.3.4.2.1. Shear methods

Soil shear strength can also be determined in-situ by means of torsional shear box, annular grouser plate and shear vane. They are explained in details by Gill and Vanden-Berg (1967). These methods basically apply similar measuring principles as those of the direct shear box. However, soil is being sheared by means of forces applied by rotation instead of transitional horizontal displacement of the direct shear box.

2.3.4.2.2. Penetration resistance

2.3.4.2.2.1. Vertical penetrometers

Soil PR is the force required to penetrate into soil (Stelluti et al., 1998) by a cone connected to a rod pushed vertically downward. A load cell with compression load type is typically used to measure force during penetration. Some penetrometers are equipped with an ultrasonic sensor to measure the distance as the cone penetrates, hence, resistance at different depths can be obtained. Another type of penetrometer cone was designed by Bengough et al. (1991), based on rotating the cone while penetrating soil, thus reducing soil-metal frictional resistance. Small variations in soil strength could be detected, but the system turned out to be too expensive for practical use.

Penetrometers are useful tools as they can identify spots of high soil strength quickly. Root growth of most crops is reduced when the soil strength is about 1500 kPa, whereas root growth of many plants stops when soil strength is about 2500 kPa (Kees et al., 2005). Penetrometers are mainly useful for comparative studies where measurement of soil strength for different scenarios is required, for example, to assess the effect of tyre type (Soane, 1973) and tyre inflation pressure on soil compaction (Mouazen and Godwin, 2009). However, PR has to be utilised with cautious, since PR is strongly influenced by soil texture, MC, BD and SOM. Literature confirms that PR increases with BD and clay content and decreases with MC and SOM (Canarache, 1990; Quraishi and Mouazen, 2010; Unger and Jones, 1998). Vaz et al. (2001) developed a soil penetrometer cone equipped with a coiled-TDR for simultaneous measurement of PR and MC. Yurui et al. (2008) developed a combined sensor system of a fringe-capacitance and penetrometer to measure PR and MC. This system was mounted on the three-point linkage of a tractor to enable on-line measurements. However, a system that accounts for the effect of soil texture, MC, SOM and BD during the measurement of PR is required.

Penetrometers are prone to errors when used in heavy and dry soils and manual penetrometers cannot be used under hard soil conditions. To overcome this potential problem, Tekin and Okursoy (2007) used the three-point linkage of a tractor to mount a hydraulic powered penetrometer connected to a load cell and computer. Hydraulic power pushes the cone penetrometer at a steady penetration speed which makes it a highly

productive method as compared to hand measurement, although it requires driving in the field.

2.3.4.2.2.2. Horizontal penetrometers

A horizontal PR measurement setup requires a cone connected to a force lever, which is connected to a load cell. It is mounted on a tractor and driven horizontally in the soil at any desired depth down to 50 cm. The speed of the tractor greatly influences PR, so the sampling rate must be adjusted to velocity of the tractor (Sun et al., 2006). Comparison of soil strength using horizontal and vertical penetrometer was studied by Hemmat et al. (2009) at different depths. It was found that due to different types of failure, horizontal and vertical PR measurements are not similar. For shallow depths (20 to 25 cm), horizontal and vertical penetration gave comparable results due to brittle failure mode in both cases, but for depths of more than 30 cm, failure mode changes from brittle to compressive with the vertical penetrometer.

2.3.4.3. Draught sensors

Draught of a soil cutting tool is commonly used to map soil resistance, incorrectly referred to as compaction. Draught is measured by commercially available or specifically designed load cells or strain gauges. Godwin (1975) used an extended octagonal ring transducer (EORT) to measure tillage forces. Richards (2000) used an EORT to measure draught of a tine and to map soil resistance. The results showed that soil texture type and other soil physical properties were not correlated to draught and that the soil type variability throughout the field could not be predicted using the draught force results. Al-Janobi (2000) combined an EORT with data logging system to measure and record on-line draught. The on-line measured draught only showed soil resistance variability and no correlation with soil physical properties were provided. Mouazen et al. (2003) carried out draught measurements with a soil sensor to measure BD as an indicator of soil compaction. They used a commercially available 5 ton single ended shear beam load cell. Mouazen and Ramon (2006) found draught alone cannot be used to produce a map of within-field variability of soil compaction. According to their findings, it is necessary to measure other influencing parameters during the on-line measurement of soil compaction and for the need for a model to calculate soil BD indicating soil compaction as a function of draught, MC and depth.

Adamchuk et al. (2004b) developed an instrument to measure linear soil resistance at different depths in the field. It consisted of a depth sensor, global positioning system (GPS), two washer-type load cells and two sets of strain gauges mounted on a custom subsoiler. This setup was able to measure soil resistance at different depths. Instruments were expanded to profile sensors enabling draught measurements at different layers (Andrade-Sánchez et al., 2007). The tine consisted of eight cutting elements connected to eight commercially available load cells to measure draught profile at depths of 7.5 to 60 cm in increments of 7.5 cm. Sharifi et al. (2007) designed a flap-faced tine with eight strain gauges, which measured the bending moment of the tine as it cut through the soil (down to 40 cm). This sensor worked in a similar fashion of that designed by Andrade-Sánchez et al. (2007).

Although the laboratory methods for the measurement of soil strength are time consuming, they provide essential information for soil and land management. In-situ measurement methods can easily be used but their main flaw is that they were not developed to account for all parameters affecting soil strength measurement, namely, MC, BD, SOM and texture. Therefore, when spatial variation in field soil compaction has to be assessed, any soil strength measurement must be accompanied with measurements of the other influencing parameters, unless there is proof of spatial uniformity of any of these parameters.

2.3.5. Electro-chemical based sensors

Fertilisers supply minerals to the soils as essential nutrient sources for agricultural production. Uncontrolled (excessive) addition of these substances causes undesirable environmental impacts together with increasing production costs, so knowledge of kind and quantity of nutrients in the soil is crucial. Routine laboratory analysis of nearly all minerals is available, but the majority of the procedures applied are time consuming and cannot be used directly in a field. Electrochemical sensors have been developed which can provide quick information of nutrient status and pH in the soil, not only for laboratory use but also for in-situ or on-line field measurement.

Among various classes of electro-chemical sensing methods, ion-selective electrodes (ISEs) and ion-sensitive field-effect transistors (ISFETs) are the most frequently used potentiometric sensors. Both, ISEs and ISFETs measure a voltage difference between sensing and reference parts of the system, which is directly related to the concentration and the activity of specific ions such as H^+, K^+, NO_3^-, Na^+, etc. Nitrate ISEs, which are highly selective to NO_3^- ions in solution, were first used around 1967 as quick and reliable alternatives to chemical-based laboratory methods for nitrate measurements (Dahnke, 1971).

2.3.5.1. Ion-selective electrodes (ISEs)

An ISE is defined as an electro-analytical sensor of the activity of a specific ion in a solution. This activity is converted into an electrical potential, which can be measured by a voltmeter. The sensing part of the electrode is usually made as an ion-specific membrane, along with a reference electrode (Figure 2.1).

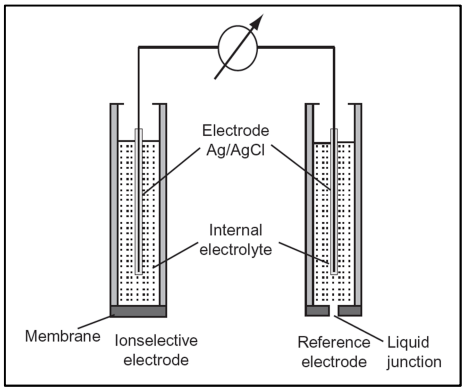

Figure 2.1. *Schematic of an ion-selective electrode (ISE) measurement.*

Theory, principles and applications of ISEs are discussed in detail in Pungor (1998; 1999; 2001), Birrell and Hummel (2000; 2001), Adamchuk et al. (2005), Kim et al. (2006) and Sinfield et al. (2010). ISEs are ion specific, each needing its own membrane permitting the passage of certain ions only. An electrical potential is established between two electrodes placed in contact with a moist soil sample or liquid soil solution. The pH electrode is the most well-known and simplest type of ISE measuring the concentration of hydrogen ions [H^+]. Key references of ISEs are given in Table 2.11.

2.3.5.2. Ion-sensitive field-effect transistors (ISFETs)

ISFETs are based on the same chemical principle as ISEs. The main technical difference between ISFETs and ISEs is that ISFETs do not contain an internal solution and the ion-selective membrane is affixed directly on the gate surface of the ISFET (Birrell and Hummel, 2000; Sinfield et al., 2010). Bergveld et al. (1998) have presented a review of theory of ISFET sensors.

ISEs and ISFETs can be affected by two factors: first – disturbances from the measurement system, for example, membrane, reference electrode and amplifier; second – soil factors hindering the attainment of electrochemical equilibrium in the measuring cell. The role of second type of factors is least studied in the literature due to complexity of measuring media. Electrode aging and mechanical wear of the sensitive membrane may result in significant changes in output. Periodic calibration in solutions with known ion activity is needed.

Interference from other undesired ions is limiting the use of ion-selective electrodes. ISEs are not completely ion-specific, but are sensitive to other ions having similar physical properties. The relative sensitivities of each type of ion-specific electrode to various interfering ions are generally known but the degree of interference depends on many factors, preventing precise correction of readings. For instance, the nitrate electrode has various ionic interferences, i.e. perchlorate, iodide, chloride and sulphate.

Due to key features of ISFETs, their application as potentiometric sensors has great advantages over conventional ISEs. For instance, small size and a solid state nature, low output impedance that reduces interference from external electromagnetic fields, mass fabrication and low cost, the possibility of integrating compensation and data processing circuits in the same chip with the sensor, high signal-to-noise ratio, low sample volume and a short response time. ISFETs might be integrated with a flow injection analysis (FIA) system for real-time soil analysis. In contrast to many other analytical methods, ISEs are capable of determining ion activities, rather than total concentration. The analyte is also not consumed in the course of the measurements and instruments are less expensive as the ones needed with other methods.

Although the soil macro nutrients, pH and Na^+ content can be measured in both exchangeable/extractable and water soluble forms by laboratory methods, these methods are time consuming, expensive and laborious. Therefore, the main emphasis of introduction of ISE and/or ISFETs in soil science is for direct soil measurements. These sensors have been used for in-situ determination of soil nitrogen/nitrate (e.g. Bound, 2006; Davenport and Jabro, 2001; Goodroad and Shuman, 1990; Thottan et al., 1994) and other nutrients such as P and K (e.g. Farrell and Scott, 1987; Grygołowicz-Pawlak et al., 2006; Wang and Scott, 2001).

On-line nutrient measurement is reported by different researchers for measuring soil NO_3^- (e.g. Adamchuk et al., 2002; Adsett and Zoerb, 1991; Kim et al., 2004; Sibley et al., 2009; Sibley et al., 2008), K (e.g. Brouder et al., 2003; Kim et al., 2007a; Kim et al., 2007b), pH (e.g. Adamchuk et al., 2007; Sethuramasamyraja et al., 2008) and P (e.g. Kim et al., 2004; Kim et al., 2006; Kim et al., 2005; Kim et al., 2007b; Kim et al., 2009). On-line measurement of soil properties using ISE/ISFET technologies includes two major operations: mechanical collection of samples that is performed while moving across the field and the real-time measurements are performed on the solution phase of the sample. This process needs a soil sampler, sampler conveyor, solution maker and measurement and registering operations (Adamchuk et al., 2007; Viscarra-Rossel et al., 2004). An operational device is developed by Sibley et al. (2009). An overview of soil nutrients and pH measured by ISEs and ISFETs is presented in Table 2.11.

Table 2.11. *Measurement accuracy reported for soil chemical properties using ion-selective electrodes (ISEs) and ion-sensitive field-effect transistors (ISFETs)*

Soil property	Mode	R^2 [a]	Key references
Ion-selective electrodes (ISEs)			
Soil NO_3^-	In-situ	> 0.75	Hansen et al. (1977); Li and Smith (1984); Bound (2006).
	On-line	> 0.41	Adsett and Zoerb (1991); Adamchuk et al. (2005); Kim et al. (2007b); Sibley et al. (2009).
Phosphorus	On-line	> 0.55	Kim et al. (2007b; 2009).
.Potassium	In-situ	> 0.60	Wang and Scott (2001); Grygołowicz-Pawlak et al. (2006)
	On-line	> 0.61	Adamchuk et al. (2005); Jianhan et al. (2007); Sethuramasamyraja et al. (2008); Kim et al. (2009).
pH	On-line	> 0.65	Adamchuk et al. (2007; 2005).
Ion-sensitive field-effect transistors (ISFETs)			
Soil NO_3^-	In-situ	> 0.54	Price et al. (2003).
	On-line	> 0.80	Birrell and Hummel (2001); Artigas et al. (2001).
pH	On-line	> 0.54	Viscarra Rossel and McBratney (1997); Artigas et al. (2001).
Potassium	On-line	> 0.55	Artigas et al. (2001).

[a] R^2 values do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.

2.4. Integration, analysis and discussion

Table 2.12 provides an overview summary of sensing technologies discussed in this report for laboratory, in-situ and on-line measurements of soil properties. The table assists providing a quick overview on the principle of technologies discussed with advantageous and disadvantages and capital cost associated. Aspects addressed in this section will be some challenges for future sensor development, comparison of accuracy of sensing technologies reviewed with conventional laboratory techniques, multiple sensors and data fusion and to what extent the requirement for sensor output demanded for precision agriculture are met with current sensing technologies.

Table 2.12. *Characteristics, applicability and cost evaluation of different soil sensors*

Technique	Measured soil properties directly or indirectly	Advantages	Disadvantages	Applicability
Visible and near infrared	Soil organic matter; soil mineralogy; plant nutrients; heavy metals; soil moisture content and pH	Fast; no sample pre-treatment required and systems are most likely portable or can be put on moving equipment for on-line measurement to provide high resolution data on soil properties	Only few clear absorption peaks on spectra that is attributed to overtones and combinations of fundamental molecular vibrations occur in the MIR range and moderately expensive	Lab, In-situ and on-line
Mid infrared	Soil organic matter; soil mineralogy; plant nutrients; heavy metals and pH	Accurate and clear absorption peaks on spectra due to the fundamental molecular vibrations	Expensive; fragile; time-consuming for sample preparation and yet cannot be used on mobile vehicle to perform on-line measurement	Lab
Electromagnetic induction	Moisture content; soil texture (clay); soil variation and salinity or Na^+ content	Non-destructive and non-invasive; light weight; easy measurements; high spatial and temporal resolution; suitable for stony and dry soils; vegetation and crop residue do not influence their response and a quick way of determining soil variability, soil layering and depth characterisation from a few cm (50 cm) to a few meters (6 m)	Moderately expensive; need site-specific calibrations; metal objects interfere their response; their signals are not linear but depth-weighted; a number of factors contribute their responses and limit their interpretation for a specific soil property; work under the assumption of low induction numbers that limit their inter-coil spacing; estimating ECa in discrete depth intervals is very difficult and soil and air temperature influence their outputs	In-situ and on-line
Ground penetrating radar	Moisture content and soil texture	A well established and active technique for subsurface sounding; able to detect geophysical anomalies in two and three dimensions; high spatial and temporal resolutions; can get more detailed information; suitable for a wide range of geophysical applications; suitable for less conductive soils such as sandy soils and modern systems offer readily automated signal interpretation and data handling	Conductive soils highly attenuate its signal and limit measurement depth to a few cm; biased estimates because a limited number of reflected waves are received by antenna due to different modes of reflected/refracted waves; sometimes not suitable for on-line measurements; many factors attenuate the radar waves and sometimes difficulty in propagation time measurement	In-situ and on-line

Table continues on next page …..

Technique	Measured soil properties directly or indirectly	Advantages	Disadvantages	Applicability
Electrical resistivity	Moisture content; soil texture (clay); soil variation and salinity or Na^+ content	Flexible for variable depth sounding; measured ECa is a linear function of depth; ECa measurement for a discrete depth interval is possible by changing inter-electrode distance; suitable for both shallow and deep soils and metal objects do not interfere their outputs	Destructive and invasive technique; requires good contact between electrodes and soils; less reliable measurements in dry and stony soils; not suitable in soils with vegetation and crop residues; a number of factors influence its output and limit their interpretation for a certain soil property	In-situ and on-line
Ion selective electrodes & Ion sensitive field effect transistors	pH; salinity; total nitrogen; phosphorous; potassium and microelements	Less expensive potentiometric instruments; simple apparatus; quick and reliable; small sizes; solid state nature; require low sample volumes; high signal to noise ratio and being used in a number of disciplines as well laboratory reference methods	Interference from other similar and undesired ions; sometimes less stable in attaining equilibrium; cell membranes, reference electrodes and amplifier may cause disturbances	In-situ and on-line
Gamma-ray spectrometer	MC; soil texture; pH; K and other minerals	Non-destructive; non-invasive and passive technique; high spatial and temporal resolution; detect geophysical anomalies; widely used in mineral explorations and radionuclides give important information about soil parent materials, clay types and geology	Expensive; not suitable in dense vegetation and ice-covered soils; interference from background radiation such as air radon; less signal intensity with increasing altitude and uncertainty from cosmic and system background	On-line
Time domain reflectometry	Volumetric soil moisture content	Accurate determination of soil moisture content, easy calibration and fast response.	Sensor response depends strongly on site specific soil properties	Lab, in-situ and online
Frequency domain reflectometry	Volumetric soil moisture content	Easy calibration; low error in measurement; quick response and easy to use as a handheld device	Not as accurate as TDR; there are issues associated with calibration as measurement is affected by other environmental factors and small area of measurement	Lab, in-situ and on-line
Tines with load cells & strain gauges	Soil mechanical resistance	Easy; accurate calibration and cheap	Not recommended for the measurement of field soil compaction variation as it is affected by the spatial variation of moisture content, organic matter content and soil texture	Lab and on-line
Penetrometers	Soil mechanical resistance	Handheld or tractor mounted; easy to use and measurement provide a fast data on variability of soil resistance and cheap	Not recommended for the measurement of field soil compaction variation as it is affected by the spatial variation of moisture content, organic matter content and soil texture	Lab, in-situ and on-line

2.4.1. Accuracy and challenges for further sensor development

Table 2.13 provides a general overview on the potential and accuracies of different sensing methods to measure soil properties under the three measurement conditions. Accuracies indicated as the number of x's were evaluated based on the determination coefficient values. In order to confirm a sensor accuracy to be within a category, accuracy category with the largest number of literature was adopted. Figure 2.2 shows the distribution of number of literature reported for different accuracy categories for the in-situ measurement of OC with vis-NIR spectroscopy. In this case accuracy is considered excellent (xxxx) as the largest number of literature fall in the R^2 category > 0.90.

This review reveals that some techniques perform better than others for the measurement of a soil property. Due to technical issues, some techniques, for example, the MIR can only be used for laboratory analysis, whereas others, for example, EMI is used for field analysis only (Table 2.13). Other methods, for example, EMI is better suited for detecting variability in soils. Another conclusion that can be drawn is that none of the sensors discussed can measure all soil properties essential for the management of the soil-plant-water system.

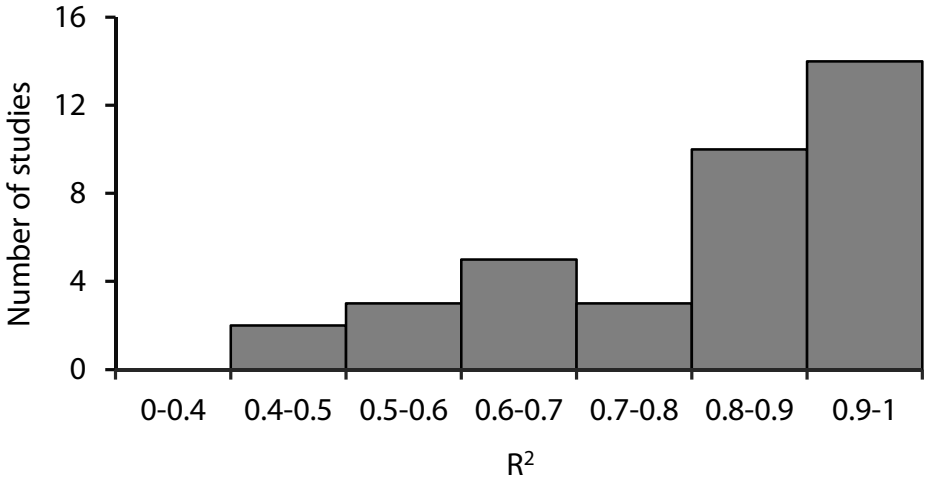

Figure 2.2. *Histogram of number of studies reported on different R^2 categories for the laboratory measurement of soil organic carbon (OC) with visible and near infrared (vis-NIR) spectroscopy taken as an example.*

The accuracy obtained for a given soil property varies with the sensing method used and with the type of measurement, for example, laboratory, in-situ and on-line methods. A sensor producing a high correlation under one set of conditions, may show a very poor performance under different conditions for reasons not yet understood. A general trend confirms that the most accurate measurement can be achieved with laboratory methods, followed successively by in-situ and on-line methods. The underperformance of the in-situ and on-line as compared to the laboratory method is attributed to environmental factors, for example, dust,

Table 2.13. *Potential of different ground-based soil sensors for the measurement of different soil properties on the basis of underlying physics of a sensing concept and their accuracy*

Soil sensors			Soil properties												
			Physical				Chemical			Mechanical		Primary macronutrients			Micronutrients
Sensor category	Sensor name	Measurement	MC	Soil texture (sand (S), silt (Si) and clay (C)	SOM or TC/OC	Soil variability	pH	CEC, Ca, Mg	Salinity or Na^+	Draught, PR	Shear strength, cohesion, friction	Nitrogen; total (TN), or nitrate (NO_3^-)	P	K	Fe, S, Mn, Cu, Zn
Reflectance based sensors	Visible & near infrared	Lab	xxxx	xxx (C), xx (Sl, S)	xxxx	-	xxx/xx	xxx	0	-	-	xxxx (TN)	xx	x	xxx-xx
		In-situ	xxxx	xx (C), 0 (Si, S)	xxx	-	xx	xx	0	-	-	xxx (TN)	xx	x	-
		On-line	xxx	-	xxx	-	xx	-	-	-	-	xxx (TN)	xx	-	-
	Mid-infrared	Lab	0	xxxx (C, S) xxx (Si)	xxxx	-	xxx	xxx	0	-	-	xxxx (TN)	xx	0	-
Conductivity, resistivity and permittivity based sensors	Electromagnetic induction	In-situ	x	x (C and Si), 0 (S)	0	xxxx	0	xx	xxx-xxxx	-	-	x (NO_3^-)	-	-	-
		On-line	xx	x	x	xxxx	0	xx	xx	-	-	x (NO_3^-)	-	-	-
	Electrical resistivity	In-situ	x	0	0	xxxx	0	-	xxx	-	-	-	-	-	-
		On-line	x-xx	x	x	xxxx	x	x	xxx	-	-	-	-	-	-
	Ground penetrating radar	In-situ	xxx	xxx	-	xxxx	-	-	xx	-	-	-	-	-	-
		On-line	xxx	-	-	xxxx	-	-	-	-	-	-	-	-	-
	Time domain reflectometry	Lab	xxxx	-	-	-	-	-	-	-	-	-	-	-	-
		In-situ	xxxx	-	-	-	-	-	-	-	-	-	-	-	-
	Frequency domain reflectometry	Lab	xxxx	-	-	-	-	-	-	-	-	-	-	-	-
		In-situ	xxxx	-	-	-	-	-	-	-	-	-	-	-	-
		On-line	xxxx	-	-	-	-	-	-	-	-	-	-	-	-
Passive radiometric based sensors	Gamma-ray or radiometrics	On-line	-	xx	-	-	x	-	-	-	-	xxx	xxx	xxx	xxx
Strength based sensors	Penetrometer tine	In-situ	-	-	-	-	-	-	-	xxxx	-	-	-	-	-
		On-line	-	-	-	-	-	-	-	xxxx	-	-	-	-	-
	Triaxial, shear box	Lab	-	-	-	-	-	-	-	-	xxxx	-	-	-	-
	Torsion, shear vane	In-situ	-	-	-	-	-	-	-	-	xxxx	-	-	-	-
Electro-chemical based sensors	Ion-selective electrodes	In-situ	-	-	-	-	xxxx	-	-	-	-	xxxx (NO_3^-)	xxx	xxx	-
		On-line	-	-	-	-	xxxx	-	-	-	-	xxx (NO_3^-)	xxx	xxx	-
	Ion-sensitive field-effect transistors	In-situ	-	-	-	-	xxxx	-	-	-	-	xxxx (NO_3^-)	xxx	xxxx	-
		On-line	-	-	-	-	xxxx	-	-	-	-	xxxx (NO_3^-)	xxx	xxxx	-

- = not measurable or not mentioned in the literature
0 = measureable with very low accuracy ($R^2 \leq 0.50$)
x = measureable with low accuracy (R^2 0.50-0.66)
xx = measureable with medium accuracy ($R^2 = 0.66$-0.81)
xxx = measureable with high accuracy ($R^2 = 0.82$-0.90)
xxxx = measureable with very high accuracy ($R^2 \geq 0.90$)

temperature, roots and stones, etc. Another source of error associated with field calibration is that samples are collected at (slightly) different locations due to poor position (Mouazen et al., 2007) and possibly at different time than measurement with a sensor. Although the latter is ignorable, a slight difference in location between sensor data and a soil sample collected for calibration may yield significant errors, due to the large variability even at small as sub-metres scale (Mouazen et al., 2007). Finally, and potentially most crucial, is the fact that only few sensing principles are able to measure a certain property directly based on the physical and/or chemical principle involved, for instance the measurement of OC and MC with vis-NiR spectroscopy and the use of ISE's and ISFET for measurement of macronutrients. Therefore, research is needed to improve current sensing technologies and develop new sensing techniques including the sensing infrastructure aiming at achieving a stable and consistent environment, which ensures a sensor to operate under varying environment in the field.

Some sensing techniques including among others acoustic, pneumatic and ground based passive radiometric based sensing using microwaves did not receive attention in this review, since only marginal advances in the development of these methods for soil analysis have been reported so far. It is worth to investigate these sensing principles further and even explore new techniques being used in other sectors for potential applications in agricultural soils.

Some properties cannot be measured directly with a sensing technique, for example, measurement of P with vis-NIR spectroscopy and this also holds for most properties measured with EMI and gamma-ray spectroscopy. The successful measurement of these properties is attributed to co-variation with other soil properties, for example, with OC in the NIR spectroscopy (Stenberg et al., 2010). As the origin of these co-variations is not yet understood nor documented in details, further research is needed. Additionally, given this limited understanding, successful calibration of sensors may only be improved by continuous calibrations using the largest possible data, which increases the cost of analysis. Still, as compared to conventional sampling methods, dense datasets that can be obtained with current sensor technologies, might increase the overall spatial estimation accuracy even if the accuracy of individual measurements is lower than existing conventional methods (Sudduth et al., 1997).

2.4.2. Reliability of "conventional" laboratory soil analysis

Accuracy and reliability of sensor data is normally compared with the "standard" procedures for obtaining soil properties, which are generally laboratory based. The assumption is that these data present the correct values of the properties under investigation and that other sensors mentioned in Table 2.13 are calibrated against these traditional methods. Many textbooks and laboratory manuals describing the procedures of soil analysis are available (e.g. Carter and Gregorich, 2007; Klute, 1986; Pansu and Gautheyrou, 2006). Although the instructions in these manuals clearly point to sources of errors and importance of reliable calibration procedures, the results of proficiency tests to assess the performance of soil testing laboratories shows that variability between (and within) laboratories can be high. Wolf et al. (1996) showed results from a testing program of 20-50 (depending on analyte tested) US laboratories; data from pH determination showed the lowest variability (RSD less

than 3%), but results for macronutrients were high (average RSD's for P, K, Nitrate N were around 25, 15 and 20%, respectively). Main factors contributing to this variability are: (1) lack of standardisation of test procedures, (2) inherent variability of the test methodology, (3) poor quality control and performance and (4) operational errors in the laboratory. More recent tests reported for European (Cools et al., 2004), US (Jacobsen et al., 2002) and Brazilian (Cantarella et al., 2006) laboratories confirm this variability, with a coefficient of variation for nitrate N up to 44 % among European laboratories. These findings indicate that utmost care has to be taken into account when assessing the quality of a soil sensor output. This is because successful calibration of studied sensors relies mainly on the accuracy of the laboratory methods, which leaves the reader unable to estimate the error attributed to the technology and associated measurement assumptions, as compared to the error from the conventional laboratory analysis.

2.4.3. Fusion

Sensors have been used with different degrees of success in assessing different soil properties (Table 2.13). It was shown in the previous chapters that due to the complex nature of agricultural soils, sensors generally react to (many) more than one property and this will strongly limit their use. As an example, readings from a frequently used sensors as the EM38 are influenced by clay content, soil salinity, MC, density and temperature. This, with varying degrees of sensitivity, might apply to some other sensors discussed in the previous chapters as well. Combining or integrating data from different soil measuring concepts, a process often referred to as "fusion" may produce complementary information on specific soil property, improve the accuracy of measurements and predictions and permit exploring a wider range of soil properties. Fusion can be achieved following different approaches:

(a) Multiple sensors where a set of sensors is assembled on the same platform to measure multiple soil properties simultaneously (Mouazen and Ramon, 2006; Taylor et al., 2006). This may allow an integrated processing of the output signals of the sensors when physical and chemical principles are matching. Research on this concept is reported by Mouazen (2009).

(b) Data fusion on soil where data are collected with different sensors on the same field. The output of the soil sensor is interpreted on an individual basis and data fusion is achieved by means of advanced multivariate statistics and geostatistics (Mahmood et al., 2009) and data fusion techniques like Kalman filter. In this instance, data from proximal soil sensing might be integrated with those from in-situ, laboratory and on-line data. However, data from different on-line sensors can also be integrated. For example, EMI scanning is recommended as the first sensing method to be implemented, by which within field variability associated mainly with texture and MC can be established. Other techniques can then be implemented to detect quantitative variation in key soil properties for soil-plant-water system management, as listed in Table 2.12.

(c) Data fusion on soil and crop (NDVI, vegetation cover, yield, etc.) are integrated with other ancillary data on field topography, weeds, pests and diseases, weather, etc. This information will differ in (spatial) resolution and time, as data collection may span more than one cropping season. This approach requires detailed knowledge of

the locations where data are collected (GPS systems) and fusion must be based on sophisticated georeferencing and geostatistical techniques, as these data differ in resolution and in time.

2.4.4. Sensor information used for site specific tillage

The traditional tillage systems to manage soil compaction are conventional, based on primary and secondary tillage, reduced tillage and no till. A fourth tillage system that starts to appear recently, with only few studies published in the last decade is designated as site specific or precision tillage, which are mostly carried out in the USA (Raper, 1999; Raper et al., 2005; Wells et al., 2001). The motivation behind site specific tillage is that economic benefit is guaranteed as only the compacted spot or layer (e.g. hard pan) is targeted during tillage operations. Raper (1999) reported a reduction in energy cost of 34% with variable-depth as compared to uniform depth tillage. Fulton et al. (1996) reported that fuel consumption could be reduced by 50 % using variable-depth tillage. The other benefit of site specific tillage is yield increase. Cotton yield increase of 10 % was reported by Raper (1999). However, to date these few studies rely on penetrometers or on EMI to map soil compaction. But, it is confirmed in literature that PR is sensitive to MC, soil texture type and SOM (Canarache, 1990; Quraishi and Mouazen, 2010; Unger and Jones, 1998). Similarly, EMI is also sensitive to other soil properties including salinity, texture, MC, SOM, etc., which makes the two techniques non-plausible to provide an accurate measurement of soil compaction (Table 2.13).

Variability in soil compaction (expressed as BD) measured with an on-line soil compaction sensor was documented (Mouazen and Ramon, 2006). This sensor is based on multiple sensor and data fusion, which enables measurement of BD, which is different in principle than all other on-line measurement system of soil compaction that measure draught by load cells or strain gauges as indicators of soil compaction level (Hemmat and Adamchuk, 2008). Multiple sensor platform and fusion of data on draught of a subsoiler measured with a load cell, a wheel gauge to measure subsoiler depth and a vis-NIR probe to measure MC are implemented in this system. A hybrid numerical-statistical model (Mouazen and Ramon, 2002) accounting for MC and depth variation has been developed to calculate BD as a function of draught, MC and depth. We believe that this system or any similar systems to measure soil compaction will enhance sensor-based or map-based site specific tillage.

2.4.5. Sensor information used for fertilisation recommendation

In order to provide farmers with fertilisation recommendation of N, P and K, ISEs and ISFETs might provide the most relevant information (Table 2.13). However, this information is limited to producing soil maps as a basis for variable rate fertilisation. The on-line and in-situ measurement of OC with vis-NIR spectroscopy might be a valuable source of additional information to tune fertiliser recommendations, to predict C sequestration effects and to provide an assessment of the quality of the soil with respect to biological activity and structural stability. In discussing the usefulness of sensor-derived information, particularly with respect to crop nutrients, the advantages of site-specific fertiliser application are prominently demonstrated. Yet, when closely examining the basis of fertiliser recommendations, we can observe that this is not a matter of "hard evidence" where the soil

property automatically leads to knowledge of what is the best or optimum fertiliser application. Recommendations are strongly dependent on soil, climate, crop and environmental conditions and, not surprisingly, methods to achieve this are called "philosophies" (Build-Up and Maintenance; Basic Cation Saturation, Per cent Sufficiency Concept; Hydroponics). Fertiliser recommendation should be based on the accumulation of the best information available and must consider profitable crop production as well as protection of the environment. This implies that not only the amount of a particular nutrient is important, but also placement, timing (application scheduling) and other field operations. This might argue the extent to which sensor-based variable rate fertiliser application (VRA) can be practically implemented in real time. However, a recent study about sensor-based VRA of P_2O_5 was published (Maleki et al., 2008), where authors reported an increase in kernel maize yield by 334 kg ha^{-1} due to VRA as compared to uniform application of P_2O_5. Hergert (1998) stresses the need for a combination of soil and plant analysis as a basis for site specific management (SSM) and VRA, indicating that an increase in both intensity and frequency of soil sampling is required for adequate SSM. The same applies for plant analysis with respect to VRA, particularly for mobile nutrients. The introduction of data fusion on soil and crop with other ancillary data as discussed earlier might be the best strategy for site specific fertilisation recommendation, which has to be obviously combined with advanced geostatistics towards map-based VRA. However, sensor-based VRA has also potential use (Maleki et al., 2008) when on-line sensors for measurement of soil properties provide accurate data on a specific soil property to enable real time VRA without the need for data on crop and other ancillary data.

It is important to note that the limited accuracy of current sensing technology matches with the accuracy of the current VRA technology and knowledge of plant response to their environment. Betteridge et al. (2008) provide an overview of sources of error that may come with site specific nutrient management, indicating that variations in nutrient application can be high, in the order of 15 % (CV) for broadcasting pellets up to 25 % (CV) for other fertilisers with less uniform granules. Band application with a drill can be more precise (CV of 7-9 %). Nutrient response curves may give sufficient information for optimum levels of application (typically within 10 % above or below a maximum) but these curves usually are site specific and generally assume non-limiting conditions of all other nutrient and soil moisture availability.

2.4.6. Sensor information used for modelling crop growth and yield

Crop models, such as the DSSAT-CSM group (Jones et al., 2003), APSIM (Keating et al., 2003) are extensively used in the analysis, evaluation and prediction of crop growth and production, on in-field scale up to regional or country levels. The information that can potentially be delivered by soil sensors for use in these models is on water and nutrients (mainly N, in relation with organic matter dynamics). Some sub-models also look at P. The WOFOST model (Van Diepen et al., 1989) addresses the macro nutrients NPK and uses output of QUEFTS (Janssen et al., 1990), which is one of the few models addressing the interaction between the main nutrients. Soil pH is an input in most models.

Plant and crop development is based on information on moisture availability by simulating storage and movement of water in the root zone, utilising known relationships between soil

physical properties and hydraulical characteristics (sometimes via pedotransfer functions). Nutrients often are considered not-limiting. Site-specific information as provided by sensors would allow estimations of spatial crop yield differences, but extreme care must be taken in the interpretation of the results. Sensitivity testing of models has shown that small shifts in input levels, for example, of available soil moisture can result in unpredictable effects on yields, often linked to climatic conditions during a season (St'astna and Zalud, 1999). Gabrielle et al. (2002) showed that *a priori* calibration of these models led to only 50 % probability of acceptable simulations, mainly caused by uncertainties in soil water components.

Examining soil properties needed to be used as input for different crop growth and yield reveals that data from different sensors listed in Table 2.13 are needed, including those from ISEs, ISFETs and vis-NIR (for N, P, K and pH), capacitance, TDR (MC). Other information can also be obtained by means of pedotransfer functions (e.g. on moisture availability).

2.4.7. Sensor information used for carbon sequestration

Sensor technology is not only needed in the traditional applications in arable farming, but will also support research and operational management in the context of new sustainability issues addressed worldwide. For example, no-till farming, combined with crop residue conservation is considered to be a system capable of sequestering carbon in the soil. Carbon credits can thus be earned, but this has created a need for quick and reliable monitoring of belowground carbon storage and dynamics. As mentioned earlier in this paper, diffuse spectral reflectance is able to quantify soil carbon (Bartholomeus et al., 2008). The patterns of soil OC sequestration in soils correlate well to plant root density and turnover times (Rees et al., 2005). Deeper root systems have the potential to sequester SOC (Smith, 2004) deeper in the soil profile, where soil OC turnover times to atmospheric CO_2 can be slower. Kusumo et al. (2010) has reported the use of vis-NIR spectroscopy to measure root density, OC and nitrogen content as a mean to predict soil carbon dynamic. A system for non-destructive in-situ carbon monitoring in soil was developed by Wielopolski et al. (2011; 2006). This system is based on inelastic neutron scattering (INS) which is a nuclear method with fast 14 MeV neutrons interacting with nuclei of the soil's elements via inelastic, elastic and capture reactions, inducing the emission of characteristic gamma rays. The gamma rays are then detected with spectroscopy using techniques explained earlier in this paper. INS measurements are unaffected by the chemistry of the elements being analysed. High correlations (R^2 around 0.99) between the INS method and conventional dry combustion techniques were found. Further research is recommended on these two sensing technologies to deliver a field sensing technology capable of gathering information of carbon sequestration.

2.5. Conclusions

The paper provided a comprehensive literature review on techniques and sensors for the measurement of soil properties, under laboratory, in-situ and on-line measurement conditions. It attempted to provide analysis of accuracy, applicability conditions and physical interpretation of why a property is successfully measured with a sensing technology.

Soil analysis with the vis-NIR diffuse reflectance spectroscopy under laboratory conditions provides the best accuracy as compared to in-situ and on-line measurement, due to excluding of environmental factors affecting accuracy. Properties with direct spectral responses in the NIR spectroscopy (e.g. OC, TN, SOM, MC and clay) are more accurately measured as compared to properties without direct spectral responses (e.g. pH and P). On the other hand, K and Na are the most difficult properties to be measured with NIR spectroscopy. Although the MIR spectroscopy is still a laboratory instrument, this technique performs better than the vis-NIR spectroscopy in measuring key soil properties due to the fact that the fundamental molecular vibrations occur in the MIR, whereas weak overtones and combinations exist in the NIR range. Taking its robustness, simplicity and portable feature into account, vis-NIR spectroscopy is particularly suitable for in-situ and on-line measurements.

Soil conductivity and resistivity based soil sensors are also widely used as non-mobile and on-line methods for soil characterisation. Soil ECa is an indirect indicator of few soil properties. However, soil ECa measured by EMI or ER is often overlooked due to the fact that a combination of factors (water content, salinity, texture, temperature, etc.) influence soil ECa to varying degrees that confound and complicate the interpolation. Specifically, EMI applications are most suitable in the areas where subsurface properties are reasonably homogeneous because measured soil depth and volume is very difficult to control. In contrast to EMI, ER methods offer options of controlling the sensed soil depth and volume. As a number of factors influence the outputs of these sensors, obtaining quantitative soil property information from ECa is difficult when all these factors contribute more or less equally. But in areas where one of the factors contributing to ECa predominates the others, the interpolations are often pretty easy and straightforward. The variation in the dominant soil property can be related with ECa measured by EMI and ER sensors quantitatively. In the latter case, salinity, MC and clay content are the soil properties that are reported to be measured successfully with ECa.

In permittivity based soil sensors, GPR is a sensor that can be used in-situ and on-line to image subsurface features, soil properties and their spatial distribution. The higher GPR frequency permits higher resolution but lowers penetration depth. Soil ECa and permittivity determine the attenuation of the radar signal. Therefore, very conductive soils (e.g. moist and clayey soils) also having higher dielectric constant can attenuate radar wave over short distances and waves penetration depth restricted to only a few centimetres. On sandy soils, GPR has the potential to better indicate the soil depth as compared to EMI devices, at which a feature (e.g. free water interface or rock layer) occurs. Notwithstanding this, in our opinion, the potential of GPR is severely limited by the nature of the soil material (clay, sands, etc.) in a field and the operation of GPR sensing is slow as well as the interpretation of the output, which is not easily automated.

Other permittivity based sensors such as TDR and FDR technologies are well established EM techniques for in-situ or in substrate level volumetric MC determination of very small volumes of soil columns. Furthermore, they can easily be automated for on-line measurement of MC especially with capacitance techniques. They can monitor temporal development of MC at one location with a high temporal resolution. Also determination of

spatial MC distribution is very labour intensive because these probes need to be installed at each measurement location. Because of soil heterogeneity, collection of enough point measurements to adequately capture the spatial trends of MC within a small field is difficult. In comparison with TDR/FDR and microwave remote sensing, GPR is an intermediate technology that can be used at field scale for quick determination of MC and other soil properties.

Gamma-ray spectroscopy is a relatively new soil property sensing technique. The presence of radionuclides (K, Th and U) in soils is believed to be associated with certain soil constituents and can relate to the mineralogy and geochemistry of soils. Numerous authors found relationships between the ROIs of gamma spectra and various soil properties such as texture and parent materials, SOM, plant available K and soil minerals. Although this technique is fairly well developed in mineral exploration, it is not yet matured and much research is needed to prove the applicability of the concept in precision agriculture.

Strength based sensors are successfully used for the measurement of soil resistance. Since laboratory, in-situ and on-line measurement methods of soil strength are affected by MC, soil texture type, BD and SOM, these methods are not recommended to measure soil compaction. Multiple sensor and data fusion is recommended for the development of a sensing system that accounts for all affecting parameters, while estimating soil compaction referred to as BD.

Electro-chemical based sensors (ISEs and ISFETs) are the only sensors that can provide quantitative information on soil nutrients comparable with conventional laboratory analysis and have successfully been used to directly evaluate soil fertility. ISEs have been historically used by commercial soil laboratories for standard soil testing as well as pH measurement. Unlike all types of soil sensors described in this paper, these soil sensors are capable for direct soil measurement. They require actual soil sampling for making solution and measuring outputs. On the other hand, these types of sensors require significant amount of time to reach equilibrium and hence stability. Although these sensors are being used on-line, but their output would not be so accurate because of the limited time available for measurement. For on-line geo-referenced measurements there is also a factor of time lag between sampling and actual ion measurement that also needs to be investigated in further research.

The review revealed that in terms of accuracy, quite a few sensing techniques show considerable potential, but there is also considerable room for improvement. An important reason for low correlations to occur might be due to the fact that only few techniques are able to measure directly a certain soil property based on underlying physical and/or chemical phenomena. Many other soil properties can only be quantified indirectly through co-variation with directly measured soil properties with which they are associated. In order to improve the performance of these sensing techniques for the measurement of properties through co-variation, in-depth research is needed to understand and quantify these correlations. Another source of poor correlation is the spatial and temporal mismatch between sensor measurement and sample collection for laboratory analysis to be used for calibration and validation of the system. It is worth mentioning that the laboratory methods,

to which current sensors are calibrated, are themselves subjected to considerable variation or error, as well.

To arrive at realistic measurement methodologies of soil properties, advanced measurement and modelling techniques might be worth considering. However, some soil properties can be measured with a single sensing technology, for example, MC can be measured successfully with vis-NIR spectroscopy. Other properties such as soil compaction (BD) cannot be measured with simple technique (e.g. PR) and multiple sensors and data fusion are recommended. Furthermore, for proper soil-plant-water management system including fertilisation management, modelling of crop growth and yield requires the fusion of data is required not only on soil, but on crop, topography, weather, yields, etc. collected at different resolutions, scales and time. Even historical data might be integrated in the analysis. To extract useful information from these multiple layers of information advanced geostatistics and data fusion technique like multivariate statistical analyses and Kalman filtering are recommended.

The accuracy analysis provided an overview of accuracy expected when adopting a technique in laboratory, in-situ and on-line, which assists the users to adopt a sensing technique for site specific application of input. Concerning the site specific fertilisation, ISEs and ISFETs together with vis-NIR techniques might be the best field methods, whereas the latter supports map-based as well as sensor-based VRAs. However, the analysis suggested that more chances for map-based variable rate fertilisation are expected as compared to sensor-based variable rate fertilisation. It was also concluded that several sensors are to be used for modelling crop growth and yield including ISEs, ISFETs and vis-NIR (for N, P, K and pH), capacitance, TDR (MC), whereas vis-NIR and combined INS and gamma rays both show high potential for measurement of carbon sequestration.

It is worth noting that successful measurement of soil properties should be performed with cost effective methods. Since advanced sensing technologies together with multiple sensors and a data fusion approach is the future direction for successful measurement system, these will be expensive for the farmer to adopt, particularly when no economic analysis is provided to prove the system to be profitable to the farmer. Therefore, future research should focus on profitability of adopting advanced sensing methods, which will advise the best model of implementation (contractor-based or purchasing-based model).

Chapter 3

Evaluation and implementation of vis-NIR spectroscopy models to determine workability

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3.1. Abstract

Quantitative information of soil properties and their spatial distribution is needed for site-specific soil management. Conventional laboratory methods to obtain high-resolution soil data are expensive and labour intensive. Visible-near infrared (vis-NIR) reflectance spectroscopy is a rapid and cost-effective technique for successful soil characterisation. The objective of this study was to determine the robustness of vis-NIR reflectance models to predict tillage (workability) related soil properties, such as texture and total organic carbon (TOC) and other common soil properties on a field scale using different types of modelling strategies in the Netherlands. For prediction of these properties, spectral data were related to soil properties using support vector regression. For this method, we evaluated the influence of calibration set on the accuracy of prediction for independent samples. The types of models included local models (LMs; models of individual fields), general models (GMs; models of combining equal proportions of samples from all fields), spiked models (SMs; using 10 samples from the target field and all samples from other fields) and true validation models (TVMs; calibration from four fields and validation in the remaining field). The main difference between these models lies in the number of soil samples that need to be taken from a specific field of interest, which determines the investments that have to be made. Results revealed that LMs gave the best results, but a large number of samples has to be taken from each field, which costs a lot of time and money. Therefore, this type of models may not be so practical for a farmer having multiple fields. The GMs showed variable accuracies for different sized models, where the accuracy increases with the number of samples. This means that a large number of samples is needed for making a good calibration model and therefore GMs may also not be so effective. TVMs are cheap to make, but the risk of wrong predictions in the target field, which is different from the calibration fields, is present. SMs yielded predictions comparable to the LMs and yielded an acceptable RMSEP with a limited number of samples per field (10 samples) for clay and TOC. This makes SMs very effective, with the potential to predict workability related soil properties with a limited number of samples in the target fields.

Keywords: visible-near infrared spectroscopy; model robustness; local models; general models; spiked models; true validation models.

3.2. Introduction

Soils generally show a high spatial variability and variations occur over short distances, vertically and horizontally (Stenberg et al., 2010). Spatial soil variability results from complex processes and mechanisms that are difficult to fully comprehend (Viscarra Rossel et al., 2006). Soil characterisation is very important for optimal soil management, to maximise crop productivity and to minimise the environmental risk from excessive inputs. In precision agriculture, quantification of variability in different soil properties is essential to vary soil tillage and distribution of inputs at desired places in the field.

Soil property information is needed for proper management, particularly with respect to tillage. The ability to predict optimum condition of soil for tillage (workability) depends on knowledge of the extent and structure of the variability in main physical characteristics (Kværnø et al., 2007). Texture clearly determines the boundaries of the ranges of soil structure, which in turn sets the physical behaviour and plays an integral role in controlling chemical and biological processes (Pagliai et al., 2004). Soil workability may be estimated using pedotransfer functions having clay, silt, sand, organic matter, gravels and tilling depth as basic input parameters (Cadena-Zapata et al., 2002; Hoogmoed et al., 2003; Kværnø et al., 2007; Terzaghi et al., 1988).

Collection of such information using conventional soil sampling and laboratory analyses is time consuming and expensive. Attempts are being made to complement or even replace the conventional methods with more efficient and less cost-prohibitive methods. Visible-near infrared (vis-NIR) spectroscopy is an effective method for rapid evaluation of different soil properties related to decisions regarding tillage and soil quality (Shepherd and Walsh, 2002). It is particularly important when a large number of observations is needed to have dense soil information to be used for precision agricultural applications. For site-specific tillage, information on basic soil properties, such as texture and organic matter, is needed with dense measurements.

The vis-NIR reflectance spectrum is known to reveal information about important soil constituents including texture and organic matter/carbon. Benefits of vis-NIR spectroscopy over laboratory methods as a rapid, easy and inexpensive method of characterising several physical, chemical and biological soil properties have been reported (Bartholomeus et al., 2008; Chang et al., 2001; He et al., 2007; Islam et al., 2003; Kuang and Mouazen, 2011; Viscarra Rossel et al., 2006). Vis-NIR spectroscopy can be used either in the laboratory, in the field (in-situ or real-time) or as remote sensing from an airplane or a satellite (Stevens et al., 2008). Remote sensing is excellent for regional- or global-scale soil sensing and mapping, but it may not provide sufficient accuracy for localised soil and land management.

To realise the effectiveness of vis-NIR spectroscopy, researchers tend to expand the scale of measurements from local to regional, national and global scales. The scale of application affects the utility of vis-NIR spectroscopy (Stenberg et al., 2010). General calibration models made from a wide range of varying soils may give improved prediction accuracies due to broad ranges of soil properties of different geographical areas. These models, however, require more universality of predictions in representative or similar types of soils. An obvious implication of this approach is that the calibration models of high generality having samples

from national or global scale may lack precision when predicting the variation at a small scale (Brown, 2007).

Spiking or augmenting is another term used in soil spectroscopy when a few reflectance spectra with corresponding soil property data are merged into a diverse existing library having spectral as well as reference soil property data to be used in local sites. Recalibration of these models (spiked models) can give good estimates of soil properties in local sites. During spiking, characteristics of local samples must be integrated in the general model (Guerrero et al., 2010).

Shepherd and Walsh (2002) were the first to suggest the idea of making a global spectral library with reference soil property data that could subsequently be spiked with local samples and recalibrated to predict soil properties in a target site. Brown (2007) used a large global library from 37 countries across the globe (over 4000 samples) to predict clay, organic carbon and clay mineralogy in a small catchment in Uganda and found often better predictions for models that were spiked with local models than the local models alone. Sankey et al. (2008) also reported improved predictions for clay and organic and inorganic carbon when the same global library used by Brown (2007) was spiked with local samples from soils of three variable landscapes, compared with using the local or global models alone. Guerrero et al. (2010) spiked the local samples into a regional library to predict Kjeldahl nitrogen and reported improved predictions with spiked models. Wetterlind and Stenberg (2010) compared local calibration models with national and reduced national models and found that local models outperformed the national and reduced national models for all soil properties. Spiking both libraries with local samples, however, reduced the root-mean square error of prediction (RMSEP) considerably and results were comparable with local models.

At regional, national and global scale a few authors have proved the potential of vis-NIR spectroscopy to estimate basic soil physical and chemical properties (Brown, 2007; Guerrero et al., 2010; Wetterlind and Stenberg, 2010). However, for a farmer, the farm or field scale is important. Fields frequently are different in texture and other soil properties and the question is of what type of models should be used. Should models for individual fields be made or general (or spiked) models to be used in all fields? We have addressed this choice in our research. Models of individual fields may be very accurate but may not be feasible because a sufficient number of soil samples from each field will be needed to make good calibration models, which is time consuming and expensive. Therefore, making general or spiked models may suffice, although reduced accuracy of predictions is obtained. To see the significance of vis-NIR spectroscopy, we used different modelling strategies mentioned in previous paragraphs to know which approach could be more realistic and would yield an optimal output with minimal sampling effort for soil properties relating to tillage and other management.

The objective of this study was to determine the robustness and practical applicability of different modelling strategies of vis-NIR spectroscopy to predict soil texture and other common soil properties for determining soil management related soil characteristics in five fields in the Netherlands. We used four types of vis-NIR spectroscopy models: local models (LMs; models of individual fields), general models (GMs; models combining samples from all

fields), spiked models (SMs; using 10 samples from the target field and all samples from other fields) and true validation models (TVM; leaving the entire target field out during calibration).

3.3. Materials and methods

3.3.1. Description of study fields

For this study we selected five fields in the Netherlands, close to the cities of Lelystad, Wageningen and Westmaas (Figure 3.1), and with a wide variation in texture. The fields are small (4 ha or less), but intensively samples. Description of the study fields is summarised in Table 3.1.

Figure 3.1. *Locations of study fields in Lelystad (fields 1 and 2), Wageningen (fields 3 and 4) and Westmaas (field 5).*

Table 3.1. *Description of study fields*

Field	Location	Crop	Area (ha)	Samples	Clay (%)	Silt (%)	Sand (%)
1	Lelystad	Onion	4	88	18.8	22.2	59.0
2	Lelystad	Carrots	1.7	72	18.9	16.4	64.7
3	Wageningen	Maize	1	24	5.0	9.2	85.8
4	Wageningen	Wheat-maize	4	77	36.9	52.6	12.8
5	Westmaas	Wheat	1.7	54	24.5	26.2	49.3

3.3.2. Soil sampling

Soil samples were collected from the 0-30 cm soil layer from Fields 3 and 4. From Fields 1, 2 and 5, we sampled two depths: 0-15 cm and 15-30 cm. In total, 315 soil samples were collected from the five fields (Table 3.1). Soil samples were collected either following transects of regular intervals (Fields 1, 2, 3 and 5) ranging from 15 m to 30 m or using a regular grid of 11 m x 11 m (Field 4). A 4-cm diameter stainless steel core was used to take soil samples, and 5-8 soil cores in a radius of 50 cm from the sampling point were taken and combined. Samples were dried in an oven at 40 °C for 72 hours and then sieved over a 2-mm mesh. Each sample was divided into two subsets: one for laboratory soil analysis and the other for spectral measurements.

3.3.3. Soil physical and chemical analyses

The following soil physical and chemical properties were determined from soil samples: texture (fractions of clay, silt and sand), soil electrical conductivity in water solution (EC), pH, total organic carbon (TOC) and total nitrogen (TN). The carbon to nitrogen ratio (C:N) was also calculated since this influences the rate of decomposition of organic matter, which results in mineralisation or immobilisation of soil nitrogen. Although soil EC and pH were not related directly with soil management and workability, they were measured as basic soil properties that can also be estimated using vis-NIR spectroscopy. Soil texture was determined using the hydrometer method (Gee and Bauder, 1986; Soil Survey Staff, 2009). Soil $EC_{1:1}$ and soil $pH_{1:1}$ were determined using an Eijkelkamp® 18.28 Multi Parameter Analyser with EC and pH probes. Soil solution of 1:1 (soil : de-ionized water) ratio were prepared for determination of both $EC_{1:1}$ and $pH_{1:1}$ as described by Soil Survey Staff (2009). Total organic carbon (TOC) was determined by sulphochromic oxidation according to ISO-14235 soil quality standard. Total nitrogen (TN) was determined from the sum of N-Kjeldahl, $N\text{-}NO_3^-$, $N\text{-}NO_2^-$, $N\text{-}NH_3^+$ and N-organic after UV digestion. Soil bulk density and moisture content are also important for tillage activities, but we did not include them in this study since they can vary strongly through time and largely depend on soil texture (clay content) and field history. Therefore, we took soil texture, organic matter and total Nitrogen as the basic soil properties for soil management.

3.3.4. Spectral measurements

Soil reflectance was measured with an ASD FieldSpec Pro FR® spectrometer (Analytical Spectral Devices, Inc., Boulder, Colorado, USA) with a spectral range of 350-2500 nm. About 20 g of soil from each sample was put in a plastic dish (2 cm deep and 4 cm in diameter). Soil samples were scanned using an ASD contact probe by putting it directly on the surface of soil sample. At the beginning of each spectral measurement session, the instrument was optimised and calibrated by measuring a dark current followed by a white reference measurement using a white Spectralon® reference panel. The instrument was recalibrated after every 10 samples. Soil spectra were interpolated to 1 nm spectral resolution, yielding a total of 2151 data points (wavelengths) per spectrum. To minimise instrument noise, each spectrum was the average of 50 internal scans. To ensure that variation within the sample is

covered, three measurements (spectra) were taken per sample placing the contact probe at a slightly different place each time.

3.3.5. Spectral pre-processing and data analysis

Spectral data of individual fields were imported in SAMS (Spectral Analysis and Management System, University of California, Davis) software. Most spectra exhibited two small step-like discontinuities at 1000 and 1830 nm, caused by transitions from one detector to another in the spectrometer itself. Spectra were corrected for this and the mean reflectance spectrum was calculated for each sample. Spectra were read in R software (R Development Core Team, 2011) to perform support vector regression (SVR) analysis (Stevens et al., 2010; Viscarra Rossel and Behrens, 2010) using the "e1071" package. SVR is a kernel-based learning method and the basic idea is to map the data into a high-dimensional feature space via nonlinear mapping and to apply linear regression in this space (Vapnik, 2000). Optimisation of parameters is an important step in SVR because these parameters influence the quality of models. The SVR parameters (epsilon and cost) should be optimised before constructing models. Furthermore, the selection of kernel type should consider the characteristic of the data source. The radial base kernel is a general purpose kernel, whereas the linear kernel is a special case of radial base kernel, where the cost parameter has the same performance as in radial base kernel (Keerthi and Lin, 2003). Both kernel types were evaluated, after which the best one was selected. First, the models were optimised for the cost parameter and next the epsilon parameter was optimised.

3.3.6. Calibration models of vis-NIR spectroscopy

We used four types of calibration models to test the effectiveness of vis-NIR spectroscopy to predict soil properties in individual fields. They included local models of individual fields (LMs); general models combining different proportions of samples from all fields, e.g. 66 % (GM66), 34 % (GM34) and 22 % (GM22); spiked models (SMs) composed of 10 samples from the target field and all samples from other fields and finally true validation models (TVM) leaving the entire target field out during calibration.

3.3.7. Prediction accuracy

The performance of the fitted models was assessed using the coefficient of determination (R^2) and root-mean squared error of prediction (RMSEP), both based on the validation data. The R^2 measures the proportion of the total variation accounted for by the model with the remaining variation being attributed to random error. The RMSEP is a measure of difference or standard deviation of difference between actually measured and predicted soil properties.

3.4. Results and discussion

3.4.1. Basic statistics of soil properties

A summary of basic statistics of all soil properties (before splitting them in calibration and validation subsets) are shown in Table 3.2. The soil of Field 3 tended to be acidic and

containing less clay (5 %) than those of all other fields. The soil of Field 3 consisted of mostly sodium and decomposed iron oxides below the plough layer because of aeolian origin. Soils of other fields tended to be slightly alkaline (pH ≥ 7.0) with more clay content (> 18.0 %). In each field, clay, pH, TOC and C:N had generally narrow ranges (SD), whereas silt, sand and EC had relatively broad ranges. Soil properties were similar for Fields 1 and 2, which were located close to each other. In contrast, the two fields in Wageningen were completely different in soil properties (Fields 3 and 4). Field 4 had the highest amount of clay (37 %) and Field 3 had the highest amount of TOC (15.8 mg g^{-1}). Field 3 also had the lowest EC value (11.5 mS m^{-1}) because of the low clay content.

Table 3.2. *Basic statistics of measured soil properties used for both calibration and validation subsets*

Statistics	Soil Properties							
	Clay (%)	Silt (%)	Sand (%)	EC (mS m^{-1})	pH	TOC (mg g^{-1})	TN (mg g^{-1})	C:N
Field 1 (number of samples = 88)								
Min	15.0	15.0	44.4	22.4	7.5	8.6	1.0	6.1
Max	23.6	32.8	68.0	45.0	8.0	12.7	1.6	11.0
Mean	18.8	22.2	59.0	33.6	7.7	10.8	1.3	8.5
SD	1.8	4.4	5.3	6.4	0.1	1.1	0.1	1.1
Field 2 (number of samples = 72)								
Min	16.0	9.0	56.4	22.2	7.6	9.2	1.1	6.9
Max	22.4	24.0	73.2	42.0	7.9	12.8	1.5	9.5
Mean	18.9	16.4	64.7	29.9	7.8	10.6	1.3	8.2
SD	1.4	3.0	3.4	5.0	0.1	1.1	0.1	0.6
Field 3 (number of samples = 24)								
Min	4.0	3.5	78.0	8.6	5.1	11.1	0.9	10.9
Max	6.0	17.0	92.0	14.4	6.2	18.7	1.4	16.7
Mean	5.0	9.2	85.8	11.5	5.6	15.8	1.1	14.2
SD	0.7	3.8	3.7	1.9	0.3	2.0	0.1	1.6
Field 4 (number of samples = 77)								
Min	25.0	41.0	3.9	19.0	6.9	9.5	1.2	5.6
Max	42.0	57.2	32.0	45.3	7.7	17.0	2.0	10.5
Mean	36.9	52.6	12.8	32.3	7.3	11.5	1.7	6.8
SD	4.1	3.6	6.3	6.1	0.2	1.7	0.2	1.1
Field 5 (number of samples = 54)								
Min	21.0	12.2	38.8	19.5	7.8	9.5	1.1	7.4
Max	28.0	37.9	63.4	31.1	8.0	11.8	1.4	9.8
Mean	24.5	26.2	49.3	24.8	7.9	10.5	1.3	8.4
SD	1.6	6.0	6.0	3.6	0.0	0.6	0.1	0.6
All fields (number of samples = 315)								
Min	4.0	3.5	3.9	8.6	5.1	8.6	0.9	5.6
Max	42.0	57.2	92.0	45.3	8.0	18.7	2.0	16.1
Mean	23.2	28.0	49.4	29.3	7.5	11.3	1.4	8.3
SD	9.3	15.3	23.1	8.0	0.6	1.9	0.2	1.7

3.4.2. Interpretation of spectral characteristics and absorption features

Mean spectra of all fields are shown in Figure 3.2. Soil reflectance was higher in Fields 4 and 5 than in the other fields. This can be attributed to the higher clay content and associated fine particle size distribution, which influence soil colour (Hummel et al., 2001). A steep increase in reflectance was noticed in spectra of Fields 4 and 5 from 540 to 800 nm, which is due to the organic carbon content. The lowest reflectance was observed in Field 3, which is caused by a higher amount of organic carbon, which decreases the reflectance. The low values from 350 through 600 nm and the steep increase in transition to the NIR region in Field 3 are due to the dark colour of organic matter (Baumgardner et al., 1985). Spectra of Fields 1 and 2 were very similar because these fields were located close to each other and had a comparable soil composition. Spectra of all fields displayed prominent dips around 1400, 1900 and 2200 nm and subtle dips around 2250 and 2300 nm. The dips between 2200 and 2300 nm are attributed to clay minerals and organic matter (Clark, 1999; Clark et al., 1990; Stenberg and Viscarra Rossel, 2010). The absorption dip at 1400 nm in Field 3 was very weak because of the low amount of clay minerals.

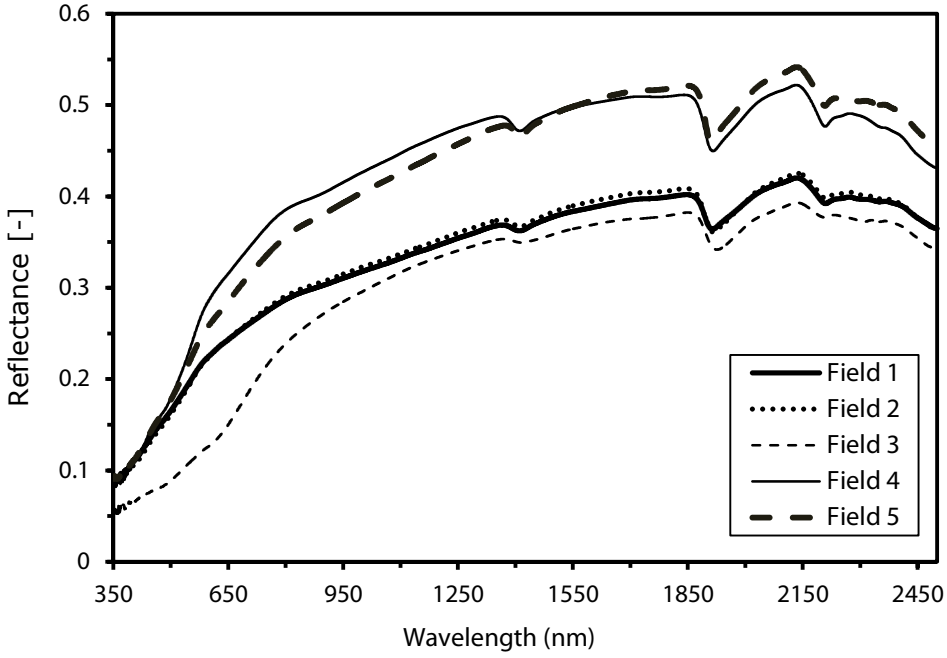

Figure 3.2. *Spectral characteristics and absorption features of mean spectra of all fields.*

3.4.3. Optimisation of parameters

The SVR models were optimised by systematically varying the cost and epsilon parameters. First, the cost parameter was varied from 0.01 to 1.01 in steps of 0.05 and the value for the cost parameter was set to the value corresponding with the highest pseudo-R^2. Next, the epsilon parameter was varied from 0.01 to 1.01 in steps of 0.02. The final models used the optimised cost and epsilon parameters to predict the soil property of interest.

To determine the type of kernel to be used to model soil properties we applied both radial and linear kernels, but the results showed that the Gaussian radial base kernel yielded lower prediction accuracies than the linear base kernel. This indicates that the general trend in the structure of the datasets is mainly linear. Therefore, we used linear base kernel for further analysis only.

3.4.4. Predictability of the local models (LMs)

As a base of reference, we developed the local models for all fields. As can be seen in the comparison later on, these models yielded the most accurate predictions. However, it is also the most expensive implementation of VIS-NIR spectroscopy, and will not result in much lower costs, since a significant number of samples needs to be analysed before a model can be fitted.

Calibration and validation results (R^2 and RMSE) of individual fields are summarised in Table 3.3. Individual fields showed good predictions for most soil properties. However, the accuracy of the predictions differed from field to field. The three fractions of texture (clay, silt and sand) were predicted with a good accuracy in all fields except Field 1, where clay showed a lower accuracy (R^2 = 0.30; RMSEP = 1.45). The highest accuracy for TOC was achieved in Field 3 (R^2 = 0.92; RMSEP = 0.77) and TN was predicted best in Field 2 (R^2 = 0.74; RMSEP = 0.06). The high accuracy of prediction for TOC in Field 3 (a sandy field) is because the range of TOC is wider and it acts as the strongest absorbent of light in the soil and will therefore dominate the spectra (Clark, 1999). The carbon to nitrogen ratio (C:N) revealed the highest accuracy in Field 1 (R^2 = 0.89; RMSEP = 1.31).

Soil properties that do not have direct responses in the spectra were also predicted with good accuracies. For instance, soil EC was predicted with an RMSEP per field below 5 mS m^{-1} and soil pH with a RMSEP below 0.17 for all fields. Although pH and EC do not have direct responses in vis-NIR spectra (Clark, 1999), they were also predicted successfully in all fields, which can be attributed to their covariance with primary soil properties that have direct spectral response in vis-NIR spectra, for instance TOC, TN and clay content (Chang et al., 2001).

Table 3.3. *Statistics of calibrations and predictions for local models (LM) with SVR using linear base kernel*

Field	Number of samples	Soil property	Calibration (two-third samples)		Validation (one-third samples)	
			R^2	RMSEP	R^2	RMSEP
Field 1	88	Clay (%)	0.66	1.03	0.30	1.45
		Silt (%)	0.92	1.43	0.68	2.42
		Sand (%)	0.89	1.91	0.70	2.77
		EC (mS m^{-1})	0.95	1.48	0.82	3.00
		pH	0.97	0.02	0.84	0.05
		TOC (mg g^{-1})	0.90	0.37	0.78	0.53
		TN (mg g^{-1})	0.91	0.04	0.66	0.08
		C:N	0.93	1.00	0.89	1.31
Field 2	72	Clay (%)	0.81	0.71	0.71	0.65
		Silt (%)	0.74	1.42	0.65	2.00
		Sand (%)	0.73	1.68	0.58	2.39
		EC (mS m^{-1})	0.82	2.19	0.87	1.78
		pH	0.72	0.04	0.77	0.04
		TOC (mg g^{-1})	0.79	0.61	0.45	0.81
		TN (mg g^{-1})	0.94	0.03	0.74	0.06
		C:N	0.51	0.38	0.16	0.54
Field 3	24	Clay (%)	0.77	0.36	0.78	0.28
		Silt (%)	0.76	2.03	0.82	2.44
		Sand (%)	0.70	2.30	0.76	2.54
		EC (mS m^{-1})	0.82	0.76	0.75	1.25
		pH	0.85	0.13	0.85	0.17
		TOC (mg g^{-1})	0.94	0.46	0.92	0.77
		TN (mg g^{-1})	0.78	0.07	0.58	0.06
		C:N	0.96	0.26	0.73	1.04
Field 4	77	Clay (%)	0.95	0.95	0.82	1.69
		Silt (%)	0.91	1.13	0.71	1.58
		Sand (%)	0.96	1.39	0.71	2.98
		EC (mS m^{-1})	0.64	3.57	0.46	4.79
		pH	0.67	0.11	0.54	0.13
		TOC (mg g^{-1})	0.82	0.78	0.73	0.84
		TN (mg g^{-1})	0.91	0.05	0.70	0.10
		C:N	0.89	0.39	0.76	0.53
Field 5	54	Clay (%)	0.94	0.39	0.72	0.88
		Silt (%)	0.65	3.47	0.56	4.12
		Sand (%)	0.69	3.34	0.59	4.14
		EC (mS m^{-1})	0.98	0.52	0.87	1.53
		pH	0.56	0.03	0.19	0.03
		TOC (mg g^{-1})	0.70	0.34	0.66	0.31
		TN (mg g^{-1})	0.63	0.04	0.47	0.04
		C:N	0.66	0.38	0.72	0.23

It should be noted that the R^2 value for predicting a certain soil property can be the same in two or more fields, whereas the RMSEP is not, because the R^2 depends on the range of that soil property within the field. Therefore, we consider the RMSEP as being the most valuable indicator of the quality of the model, since this will indicate the quality of the estimation of the soil property in question, rather than evaluating if it is useful to analyse the variability within a field. Having a low R^2, but good RMSEP simply indicates that the predicted values are good, but the field is rather homogeneous, raising the question whether precision farming is useful anyway.

In general, all soil properties were predicted with good accuracies using the LMs, with an occasional exception for a certain property in a single field (e.g. clay in Field 1 and pH in Field 5). In particular, soil texture (clay, silt and sand), TOC and EC showed good results in most fields. Therefore, soil properties related to tillage and other management practices can be successfully estimated using the LMs of vis-NIR spectroscopy. An obvious implication of this type of modelling strategy is that it needs a good number of samples from each field to make calibration and validation subsets and therefore is very expensive when a large number of fields is to be characterised.

3.4.5. Predictability of the general models (GMs)

Validation results in terms of RMSEP of LMs, three types of general calibration models (i.e. GM66, GM34 and GM22), SMs and TVMs are shown together in Figure 3.3.

As expected, a general decrease in accuracy can be seen when GMs were used, but the increase in RMSEP was limited, resulting in prediction accuracies that are still acceptable and within the range of what is typically achieved in the laboratory analysis. For all GMs, the RMSEP for clay never increases with more than 1 %, whereas for silt and sand the RMSEP increases with a maximum of just below 3 % and just over 4 % respectively.

The decrease in prediction accuracy was lowest for the GM66 predictions, showing that adding more data to the calibration dataset yields better predictions. This is the result of inclusion of sufficient variability in the calibration models from the target field. The accuracy of predictions was decreased approximately linearly by decreasing the number of samples, although this trend was not true for all soil properties and in all fields. For instance, clay, silt, sand and pH in Field 4 were predicted with a similar accuracy in GM66, GM44 and GM22 models. These results were also similar to those found in the LMs (Figure 3.3) for these soil properties with slightly lower accuracies. This might be due to a clayey texture of Field 4 with wider ranges in soil properties.

Although we compared the prediction ability of the GMs of three different compositions, the reader should be aware that the validation sets were not always the same, since the samples that were not included in the calibration model, were all used for validation. This may not provide a true comparison among these GMs, but the fact is that the number of samples in the validation models is large enough to get reliable estimates for the different model sizes.

Above results show that increasing the variation in the GMs by increasing the number of samples decreases the RMSEP of predicted soil properties. The reason is that including more samples in a GM from a target field induces more variation in the model enhancing its ability to predict similar soil properties with a better accuracy. This also reduces the effectiveness of vis-NIR spectroscopy when many more samples are needed for making general calibration models.

3.4.6. Predictability of the spiked models (SMs)

For the SMs, we combined 10 selected samples from the target field with all samples from all other fields. This gave prediction accuracies comparable to the GM66 models for most soil properties (Figure 3.3). For TOC and TN the RMSEP was more comparable to the results obtained with the GM34 model. Furthermore, the SMs were still well capable to describe the within field spatial variation in soil properties. Although many samples were needed for the construction of the calibration dataset, the results of the SMs showed that once a reasonable dataset was constructed, new fields can easily be added by selecting only a limited number of sample points. This would require a higher initial investment, but after that the costs for additional fields are much lower than for the other models, without loss in prediction accuracy.

Preferably, the small number of samples should be selected in such a way that it represents the variation within the entire field as good as possible. The soil properties that have good prediction accuracy using the SMs have a factor lower RMSEP of the standard deviation than the soil property in the individual field. It means that the SMs can be used to predict soil properties if soil samples covering the whole variation in the field are used for spiking. Random selection of samples for spiking may not yield better soil property predictions. A lower accuracy in the SMs than the LMs may be attributed to the uneven distribution of soil properties across the fields. The prediction accuracy may be increased if fields are not much different in soil properties from each other.

Similar or a slightly lower accuracy is acceptable, since when we need only 10 samples from the target field, which saves sampling time and soil analysis cost. Therefore, spiking is a valuable method for determining field-scale soil properties using vis-NIR spectroscopy. A slight loss in accuracy has to be accepted, but the RMSEP is still acceptable for most soil properties.

3.4.7. Predictability of true validation models (TVMs)

Leaving one entire field out from the calibration model and predicting soil properties in that field, resulted in the poorest soil property estimates (Figure 3.3). The RMSEP for all soil properties were highest using TVMs for most soil properties, and the models failed to predict the spatial variation within an unknown field. Especially the RMSEP for clay, silt and sand in Field 3 and 4 showed very large errors. The reason for this is that the three factions of texture were much higher/lower in these fields than the fields used in the calibration models.

Therefore, TVMs are unsuitable to predict very high or very low ranged soil properties with a different ranged calibration model.

3.4.8. Comparison of the models

Comparing the different models, the lowest RMSEP was obtained for the LMs despite narrow ranges of soil properties within a field. The outcome endorses the site-specific nature of the suite of soil sensors used in precision agricultural applications. The reason is that the LMs can integrate the characteristics of local sites better than the GMs and SMs. In addition, soil samples in the LMs are considerably more similar to the validation samples than the samples from other fields. Furthermore, using the TVMs without including any samples from the target field, the worst results were obtained, which is logical because the models do not describe soil variability in that field. For successful calibration, models should contain sufficient variation from the target fields where the calibration models will be used for prediction. This results is consistent with those of Duckworth (1998) and Viscarra Rossel et al. (2008).

The accuracy of the GMs and SMs was slightly lower than for the LMs. The reason of the low accuracy for these models is due to uneven distribution of soil properties. The ranges of soil properties within individual fields are narrow and wider across fields. Wider ranges across fields make the calibration samples of GMs and the SMs more dissimilar from the validation samples of individual fields. Fields having all ranges of soil properties can give better accuracies for the GMs and SMs because the calibration models with evenly distributed soil properties generally provide more accurate calibration models (Chang et al., 2005). These results are consistent with those of Wetterlind and Stenberg (2010) and Stenberg et al. (2010), who reported that models of individual fields (LMs) with relatively narrow ranges of soil properties (lower SD values) produced better predictions than the GMs made by soil samples collected from a broad geographical area with relatively wide ranges of soil properties. Results are not consistent with those of Brown (2007) and Sankey et al. (2008), who reported improved results using GMs and SMs with the local samples.

In summary, the LMs give the best results, but a large number of samples has to be taken that costs a lot of time and money. The GMs (GM22, GM34 and GM66) show variable accuracies for different sized models, where the RMSEP decreases by increasing the number of samples. TVMs are cheap, but there are big risks for making wrong predictions and may only be applicable if the target field is very similar to those used for the calibration model. However, spiking (SMs) is very effective and gives an acceptable RMSEP with a limited number of samples per field (10 samples), although a generally lower accuracy has to be accepted. But, if fields are much different in soil properties, the prediction error (RMSEP) may become unacceptably high.

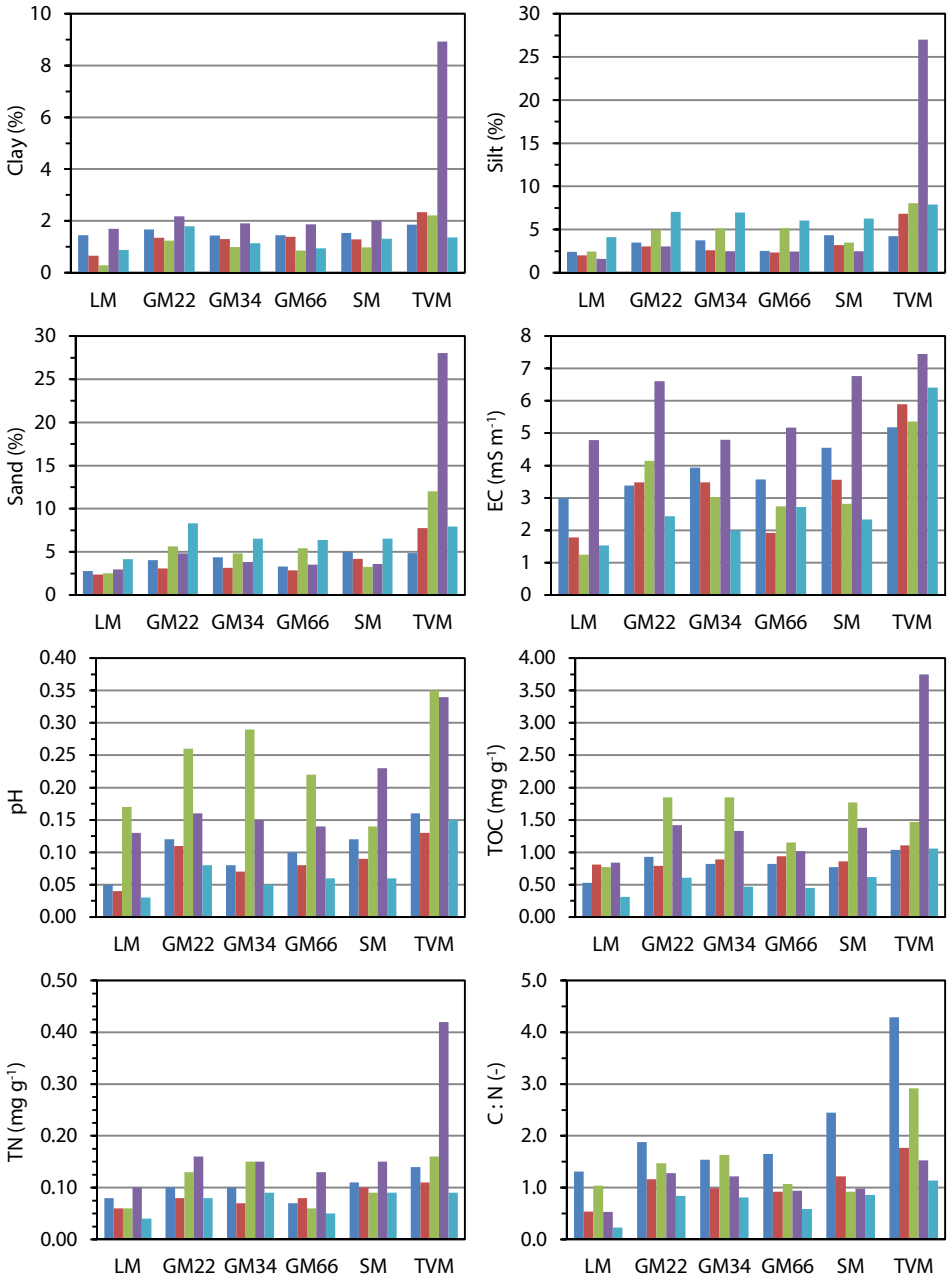

Figure 3.3. *RMSEP per field for different models (LMs, GMs, SMs and TVMs) for the major soil factors influencing workability and other soil factors. In legend: = Field 1, = Field 2, = Field 3, = Field 4 and = Field 5.*

3.5. Conclusions

In this study, we evaluated the robustness of vis-NIR reflectance spectroscopy to predict tillage or workability related and other common soil properties using four types of models: local models (LMs), general models (GMs; GM66, GM34 and GM22), spiked models (SMs) and true validation models (TVMs).

Focussing on tillage related soil properties (e.g. clay and TOC), results revealed that LMs gave the best results, but a large number of samples has to be taken from each field that costs a lot of time and money. GMs also gave acceptable RMSEP for prediction, but more samples were needed for making a better prediction model. On the other hand, the SMs gave comparable results as the LMs and yielded an acceptable RMSEP with a limited number of samples per field (10 samples) for clay and TOC and other soil properties. The SMs are therefore very effective, achieving prediction accuracies that are acceptable for management decisions. The SMs have the potential to predict workability related and other common soil properties with a limited number of samples in the target fields.

3.6. Acknowledgements

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Chapter 4

Proximal gamma-ray spectroscopy to predict soil properties using windows and full-spectrum analysis methods

To be submitted to "Sensors" Journal as:

Hafiz Sultan Mahmood, Willem B. Hoogmoed and Eldert J. van Henten

4.1. Abstract

Fine-scale information on soil properties is needed for successfully implementing precision agriculture. Conventional soil sampling methods to obtain soil data are labour-intensive and expensive. Proximal gamma-ray spectroscopy has recently emerged as a promising tool to collect fine-scale soil information. Our objective was to evaluate a proximal gamma-ray spectrometer to predict several soil properties using energy-windows and full-spectrum analysis methods in two differently managed sandy loam fields: conventional and organic. Both methods yielded comparable predictions when regressed against soil properties. In the conventional field, both methods predicted clay, pH and total nitrogen with a good accuracy ($R^2 \geq 0.56$) in the top 0-15 cm soil depth, whereas in the organic field, only clay content was predicted with such accuracy. The highest prediction accuracy was found for total nitrogen ($R^2 = 0.75$) in the conventional field in the energy-windows method. Other soil properties showed variable prediction accuracies in both fields and methods. Prediction accuracy of soil properties was higher in the individual fields than when combining them. Furthermore, soil properties in the top 0-15 cm soil depths were predicted better than in the 15-30 cm soil depths for individual and combined fields. This implies that gamma-ray spectroscopy can generally benefit soil characterisation for annual crops where the condition of the surface layer and the seedbed is important. Small differences in soil structure (conventional vs. organic) cannot be determined. As for the methodology, we conclude that the energy-windows method can establish relations between radionuclide data and soil properties as accurate as the full-spectrum analysis method.

Keywords: proximal soil sensing; gamma-ray spectroscopy; energy windows; full-spectrum analysis; prediction of soil properties.

4.2. Introduction

Characterisation of spatial variability in soil properties is crucial for farmers to reduce the risk of crop failure, to improve the efficiency of decision making and to benefit in both economic and environmental sense (Blackmore, 2000). Collection of fine-scale information on soil properties, using conventional soil sampling and laboratory analyses, is time consuming and expensive. More efficient methods to attain this information are essential for soil monitoring, modelling and precision agriculture (Viscarra Rossel and McBratney, 1998).

Proximal soil sensors in precision agriculture have capabilities to provide soil information with high spatial and temporal resolution and to explain variations in soil properties (Hummel et al., 1996). These soil sensing methods involve less interfering factors, such as clouds and vegetation cover and are advantageous over aerial and satellite remote sensing methods (McBratney et al., 2003). Using proximal sensors, therefore, less ambiguous relations can be established between sensor-output and soil properties (Barnes et al., 2003). Gamma-ray spectroscopy, also known as radiometrics, is one of the ground-based proximal soil sensing methods that can provide information on soil properties at a high spatial resolution.

Gamma rays are quanta or photons of high energy and short-wavelength electromagnetic radiation emitted from naturally occurring isotopes (Ward, 1981). Radioactive isotopes of elements that emit gamma radiation are called radionuclides. Many radionuclides occur naturally, but only potassium (K) and the decay series of uranium (U) and thorium (Th) produce gamma rays of sufficient energy and intensity to be measured with gamma-ray spectroscopy. These radionuclides are present in soils and rocks in the form of ^{40}K, ^{238}U and ^{232}Th isotopes in varying amounts. Other man-made or human induced radionuclides are also present in soils in different regions of the world, such as ^{137}Cs (a radioisotope of caesium) that has been deposited on soils due to nuclear tests, warfare and accidents like Chernobyl (IAEA, 2003).

Radiation not originating from the earth's surface is regarded as background. The main sources of background radiation are atmospheric radon (^{222}Rn), cosmic sources and instrumental background. A number of factors attenuate gamma-ray emission. In soils, water content and bulk density are the major factors that attenuate gamma-ray emission (Taylor et al., 2002).

The abundance and distribution of radionuclides reflect geomorphic and weathering processes (Dickson and Scott, 1997; Wilford et al., 1997). Sandy soils with leached profiles, are readily recognised by a low gamma-ray count rate (Cook et al., 1996). In clayey soils, ^{232}Th can adsorb onto clays and hence clay content can be mapped from ^{232}Th concentration (Wedepohl, 1978). Potassium feldspars occur in granites. Freshly weathered granite with a shallow soil profile has a high ^{40}K count rate (Cook et al., 1996; Wilford and Minty, 2006). Ferruginous materials or gravels from a deeply weathered profile are rich in ^{232}Th and ^{238}U counts (Cook et al., 1996; Dickson and Scott, 1997). The concentration of ^{40}K, ^{232}Th and ^{238}U contents in soils and rocks generally increases with increasing silica content (Wilford and Minty, 2006). Soil texture is more likely to contribute directly to the radiometric data than the other soil properties, such as organic carbon or pH (Megumi and Mamuro, 1977). Once a

relationship is established with soil texture, many other indirect relationships between soil properties and radiometric data are apparent (Wong and Harper, 1999).

Gamma-ray spectroscopy is a relatively new approach in soil characterisation and the focus has been to evaluate the technology in a soil mapping framework. Several authors have identified relationships between airborne gamma-ray data and soil properties. Most of them established correlations between soil properties and energy-windows (EWs) of radionuclides, such as ^{40}K (EW_K), ^{238}U (EW_U) and ^{232}Th (EW_{Th}). Cook et al. (1996) distinguished highly weathered residuum and fresh material from granitic outcrops and identified soil parent materials using EWs of airborne gamma-ray spectroscopy. McKenzie & Ryan (1999) predicted total P content (R^2=0.78) with EW_K when combined with several parameters of a digital elevation model. Pracilio et al. (2003) found a correlation between the EW_{Th} and clay content (R^2 = 0.68) using linear regression in highly weathered soils. In a later study, Pracilio et al. (2006) related the EWs of airborne gamma-ray spectra with clay content and plant available-K in highly weathered and varying textured farmland. Airborne gamma-ray studies in young soils were reported from Wales and England where Rawlins et al. (2007) found good correlations of EW_K and EW_{Th} with soil parent materials and soil texture.

Although airborne gamma-ray spectroscopy has been used to find relationships with soil properties, it cannot distinguish small variations in soil properties within a field. Higher elevation causes more attenuation, lowers the spatial resolution and thus lowers the intensity of signal, which is reduced to half above 121 m in air (Cook et al., 1996).

Proximal gamma-ray spectrometers gained interest since the last decade for soil property mapping with spectral EWs of radionuclides. Wong & Harper (1999) found a good correlation (R^2 = 0.93) between plant available-K and EW_K on a large farm in Australia. The EW_K was further found to be related with clay content, pH, Fe, P and organic carbon.

Attempts were also made to relate gamma-ray data with soil properties using full-spectrum analysis (FSA) methods. Viscarra Rossel et al. (2007) analysed the data of a proximal gamma-ray spectrometer, using an FSA method based on partial least squares regression (PLSR) and found robust predictions for clay, sand and Fe content ($R^2 \geq 0.63$) in the top 0-15 cm soil depth. An FSA method was proposed by Hendriks et al. (2001) to relate radiometric data with environmental attributes. This method has been reported to relate soil texture (clay content), organic matter and soil nutrients with variable success (Van Egmond et al., 2010). Van der Klooster et al. (2011) determined clay content using gamma-ray spectroscopy combined with the FSA method in three marine districts in the Netherlands at field, regional and district levels.

We expect that gamma-ray spectroscopy can enhance spatial resolution of soil data at the field scale when analysed with either the EWs or the FSA methods. Although a certain amount of relevant information may be lost in the EWs method, this serves as a simple and reference method to relate radiometric data with soil properties. A proximal gamma-ray spectrometer commonly used in the Netherlands, the Mole[1], was developed for the FSA

[1] The Mole is a gamma-ray spectrometer developed and commercially used by The Soil Company, Leonard Springerlaan 9, 9727 KB, Groningen, the Netherlands.

method (Van Egmond et al., 2010) and to the best of our knowledge no attempts have been made to evaluate it with the simpler EWs method.

Our objective was to evaluate a proximal/ground-based gamma-ray spectrometer to find quantitative relationships between radiometric data and soil properties in two closely located sandy loam fields in the Netherlands. Our further intent was to compare the abilities of two data analysis methods: the EWs and the FSA, to predict soil properties using the radiometric data acquired by this spectrometer.

4.3. Materials and methods

4.3.1. Study fields

This study was conducted at the experimental farm of Wageningen University, the "Broekemahoeve", near Lelystad (52°32'35.67"N, 5°34'26.50"E), in the Flevoland province of the Netherlands. Total study area was about 4 ha, comprising a conventionally managed and an organically managed field, approximately 100 m apart. In the conventional field, fertilisers and chemicals were applied for nutrients and to control insects, diseases and weeds. The organic field was managed without chemicals. Soil texture of the fields was sandy loam with varying amount of seashells. Fields were under a wheat crop and measurements were carried out after the harvest in the year 2010.

4.3.2. Acquisition of gamma-ray data

The gamma-ray data were acquired using a portable passive gamma-ray spectrometer, the Mole, equipped with a CsI(Tl) scintillation crystal detector. The CsI(Tl) crystal (70 x 150 mm) is coupled with a photomultiplier unit and a multichannel analyser (MCA) system to acquire real-time gamma-ray spectra. The MCA system consists of 256 energy channels between 0 and 3.0 MeV. The spectrometer can be mounted on a tractor, car, and quad bike or can even be used manually. In this study, the spectrometer was moved in the field at about 1.2 m s^{-1} mounted on a wheel barrow at about 30 cm height. The field of view of the spectrometer at this height was about 3 m. In each field, eight rows were selected for data collection, which were about 10 m apart along the length of the fields. The radiometric data were collected at 1 Hz frequency from about 4000 points from both fields together with the associated GPS locations. These data were logged every second directly into a laptop computer.

4.3.3. Soil sampling and laboratory analyses

Thirty six locations in each field were selected for soil sampling using transects of regular intervals (~15 m). From each sampling location, 5-8 soil cores were collected from two depths: 0-15 cm and 15-30 cm, in a radius of 1 m from the sampling node and homogenised. A total of 144 samples from both depths were collected from both fields. Soil samples were air dried, passed through a 2-mm sieve and analysed in the laboratory for determining soil texture, electrical conductivity (EC), pH, total organic carbon (TOC) and total nitrogen (TN). Soil texture was determined using the hydrometer method (Soil Survey Staff, 2009). Soil EC and soil pH were determined using an Eijkelkamp® 18.28 Multi Parameter Analyser with EC

and pH probes. Soil solutions of 1:1 (soil : de-ionized water) ratio were used to determine both EC ($EC_{1:1}$) and pH ($pH_{1:1}$) as described by Soil Survey Staff (2009). TOC was determined by sulphochromic oxidation according to ISO-14235 soil quality standard. TN was determined from the sum of N-Kjeldahl, $N\text{-}NO_3^-$, $N\text{-}NO_2^-$, $N\text{-}NH_3^+$ and N-organic after UV digestion.

4.3.4. Independent calibration and validation subsets

Usually, the calibration and validation measurements are taken separately. For instance, from calibration locations, the gamma-ray measurements are taken for about five minutes, whereas the measurements from the validation locations and/or from the rest of the field(s) are completed while going. The discrepancy of both methods is avoided in this study which shows the real effectiveness of the gamma-ray spectroscopy. Therefore, all gamma-ray measurements were taken real-time from both fields. The field of view of gamma-ray spectrometer allowed us to match soil samples within its sensing span. In a radius of 3 m around each soil sampling location, gamma-ray measurement points were picked up and averaged to yield a mean gamma-ray spectrum that was assigned to that soil sampling location. We assumed that this mean spectrum would be representative for the nearby (within 3 m radius) soil sampling location. In each field, soil samples from all sampling locations with associated gamma-ray measurements were randomly divided into two subsets: half of them for calibration and the remaining half for validation. Similarly, half of the total samples from both fields were used for calibration and the remaining half for validation for combined fields. It should be noted that a few soil sampling locations were farther than 3 m from the gamma-ray measurement points. Soil samples from those soil sampling locations were not used for calibration, but they were used for validation.

4.3.5. Spectral data pre-processing

The aim of spectral pre-processing was to reduce statistical noise, to increase signal-to-noise ratio and to identify the radionuclide peaks in the measured spectra. We transformed multichannel gamma-ray data into corresponding energies using Equation 4.1:

$$E_\gamma\ (MeV) = 0.0117 \times \gamma \qquad \textit{Equation 4.1}$$

where, E_γ is gamma-ray energy in MeV and γ is the channel number from 1 through 256. Each channel, therefore, represents a band width of 0.0117 MeV. Gamma-ray counts in each channel were converted to count rates dividing by the life-time of a measured spectrum. A spatial filter of the moving average of seven gamma-ray sampling points was used to reduce the noise and acquire stability in gamma-ray spectra. A moving average of five energy channels was also calculated within each spectrum to further de-noise and smooth the spectra and to identify peaks. The processed spectra were used for further analysis.

4.3.6. Energy-windows (EWs) method

Spectral EWs of radionuclides ^{40}K, ^{238}U and ^{232}Th (also referred to as EW_K, EW_U and EW_{Th}) were determined by summing the intensity of gamma-ray counts on the energy spectrum surrounding the peaks of radionuclides as suggested by Grasty et al. (1985). Total

radioactivity in terms of total counts (TC) was also used as a broad window. The EWs with their photo-peak centres are shown in Table 4.1. First, the effects of other radionuclides in a certain EW of an element were removed using sensitivity analysis (IAEA, 2003). Second, the count rates were converted to elemental concentrations using stripping algorithms as instructed in IAEA (2003). Stripping factors (e.g. α, β and γ) and sensitivities were determined from the standard[2] spectra of the spectrometer (Figure 4.1).

Table 4.1. *Conventional EWs in gamma-ray spectroscopy (IAEA, 2003)*

Radionuclide	Radioisotope	Photo-peak centres (MeV)	Energy window (MeV)
Potassium (^{40}K)	^{40}K	1.46	1.36-1.56
Uranium (^{238}U)	^{214}Bi	1.76	1.66-1.86
Thorium (^{232}Th)	^{208}Tl	2.61	2.41-2.81
Total count	-	-	0.04-2.81

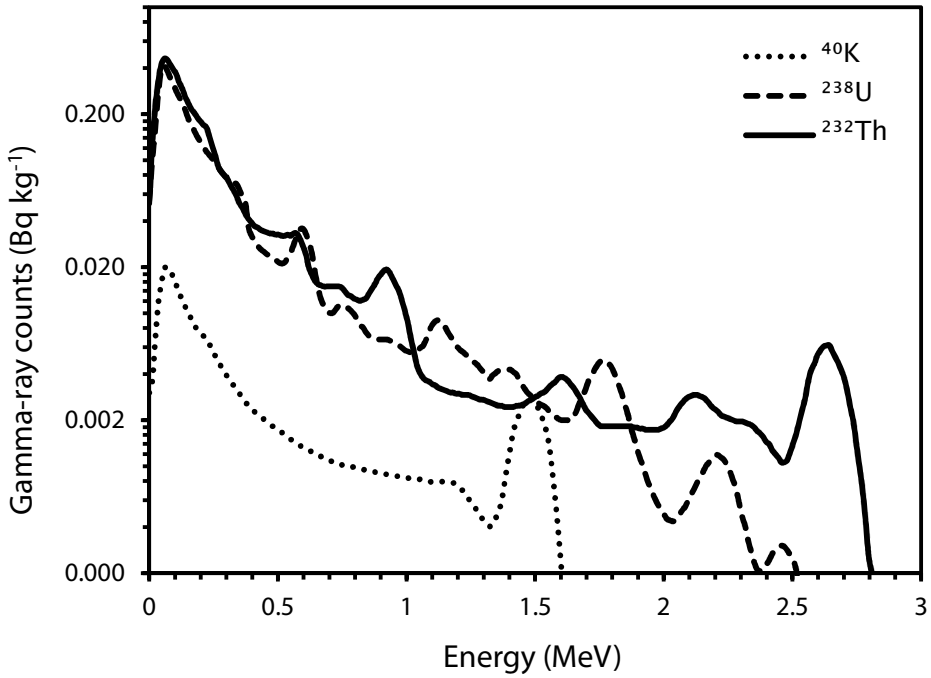

Figure 4.1. *Standard spectra of radionuclides ^{40}K (dotted line), ^{238}U (dashed line) and ^{232}Th (solid line) collected by the Mole at 1 Bq kg^{-1} activity concentration in the calibration setup. Reprinted from Van Egmond et al. (2010) with permission.*

[2] A standard spectrum is the pure response of a detector system to 1 Bq kg^{-1} source of a given radionuclide in a given geometrical setting (Hendriks et al., 2001).

4.3.7. Full-spectrum analysis (FSA) method

The full-spectrum analysis (FSA) method incorporates information from nearly the entire gamma-ray spectrum. The FSA method can be based on a multivariate calibration method (Viscarra Rossel et al., 2007) or on a simulation theory (Hendriks et al., 2001). The FSA method based on the multivariate statistics does not identify individual correlations of radionuclides with a certain soil property; rather it establishes a relationship between a soil property and the entire gamma-ray spectrum. In this study, we used the FSA method based on Monte Carlo simulations of radiation transport developed by Hendriks et al. (2001). This FSA method yields concentrations of radionuclides (i.e. ^{40}K, ^{238}U and ^{232}Th) just like the EWs methods, which makes the comparison between the two methods easy. In this method, the standard spectra of ^{40}K, ^{238}U and ^{232}Th, with an activity concentration of 1 Bq kg^{-1}, are fitted to the measured spectrum using a Chi-square (χ^2) algorithm (Hendriks et al., 2001). Multipliers of the standard spectra of the radionuclides are thus generated that are equal to the activity concentrations of these radionuclides in Bq kg^{-1} units.

4.3.8. Data analysis

Exploratory bivariate analysis, based on linear regression and correlation, is a common method of data analysis to explore relationships between radiometric data and soil properties (Wong and Harper, 1999). In calibration datasets, concentrations of radionuclides obtained from the EWs and the FSA methods were linearly regressed to soil properties to expose correlations between them. The developed regression models were then used to predict soil properties in the validation datasets. The strength of relationships between predicted and measured soil properties was tested with coefficient of determination (R^2) and the root-mean squared error of prediction (RMSEP). Moreover, the statistical significance of the models was also tested using F-statistics values at 5 % and 1 % significance levels. Finally, we calculated the ratio of per cent deviation (RPD), which is a ratio of standard deviation of a reference soil property and its RMSEP, to test the prediction ability of models. RPD values greater than 1.4 can potentially be used for prediction of soil properties (Viscarra Rossel et al., 2007).

4.4. Results and discussion

4.4.1. Study fields and descriptive statistics of soil properties

Locations of about 4000 proximally sensed gamma-ray measurements and 72 sampling locations are shown in Figure 4.2. Descriptive statistics of laboratory measured soil properties are given in Table 4.2. Soil properties showed overall narrow ranges. All soil properties of both fields showed similar statistics because both fields were located nearby. The widest range was found for sand content and the narrowest for the pH in both fields. The amount of TOC was slightly lower in the 15-30 cm soil depth in both fields because fertilisers and manures are not applied so deep.

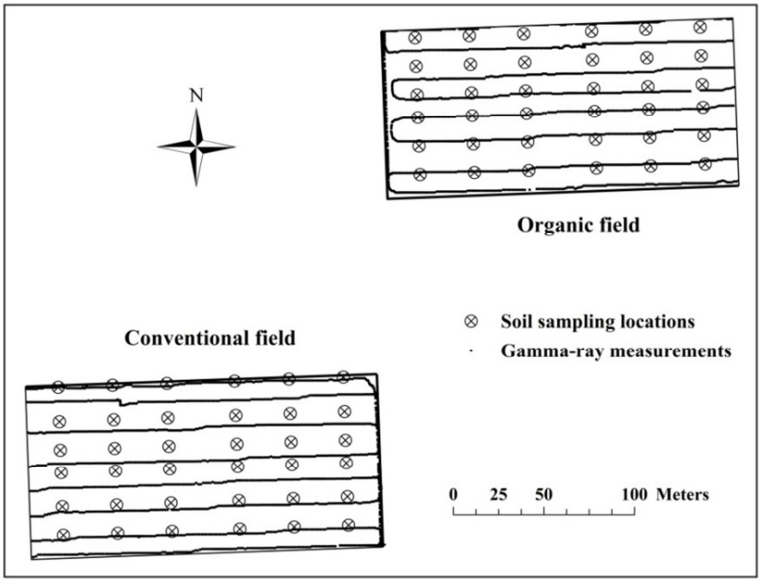

Figure 4.2. *The study fields are shown with soil sampling locations (circles with crosses). The black dots (as shown in lines) are gamma-ray measurement points measured every second in the field.*

Table 4.2. *Descriptive statistics of soil properties in both fields*

Soil property	Conventional field (n = 36 for each depth)				Organic field (n = 36 for each depth)			
	Min	Max	Mean	SD	Min	Max	Mean	SD
0-15 cm soil depth								
Clay content (%)	16.0	22.0	18.9	1.55	17.0	22.4	19.7	1.38
Silt content (%)	15.0	25.0	19.5	2.38	9.0	24.0	14.9	3.56
Sand content (%)	53.0	68.0	61.5	3.48	56.4	73.2	65.4	4.44
EC (mS m^{-1})	37.0	45.0	40.6	1.96	27.0	42.0	33.8	4.00
pH	7.6	7.7	7.6	0.02	7.6	7.8	7.7	0.06
TOC (mg g^{-1})	11.3	12.7	12.0	0.37	9.4	12.8	11.4	0.92
TN (mg g^{-1})	1.2	1.5	1.3	0.06	1.3	1.5	1.4	0.06
15-30 cm soil depth								
Clay content (%)	15.8	23.0	18.4	1.61	16.0	19.4	18.1	0.96
Silt content (%)	16.0	28.0	21.6	2.61	15.0	19.7	17.9	1.06
Sand content (%)	50.2	67.0	60.0	3.82	61.3	69.0	64.0	1.59
EC (mS m^{-1})	23.0	35.0	29.6	2.55	22.2	29.5	26.0	1.90
pH	7.8	8.0	7.8	0.04	7.8	7.9	7.8	0.02
TOC (mg g^{-1})	8.6	10.9	9.9	0.57	9.2	10.3	9.7	0.22
TN (mg g^{-1})	1.1	1.6	1.3	0.16	1.1	1.3	1.2	0.06

4.4.2. Description of gamma-ray spectra

Raw gamma-ray spectra measured every second were very noisy (Figure 4.3a). Spatial filtering of spectra using seven point moving average removed some of the noise and reduced fluctuations between the consecutive energy channels (Figure 4.3b). Performing moving average of five channels within each spectrum yielded further smoother spectra and improved signal-to-noise ratio and well-shaped peaks were visible (Figure 4.3c). Smoothed spectra also improved correlations between radionuclides concentrations and soil properties. The amount of noise in the gamma-ray spectra is due to the sensitivity of measurement. The sensitivity of gamma-ray measurements depends on the detector volume and the sampling period (Cook et al., 1996). The detector volume is fixed and therefore longer sampling period (time) can improve the measure of certainty. To increase the sampling period, however, data acquisition speed should be reduced, so it will cost more time for scanning a field. The certainty in gamma-ray measurement is therefore a compromise between data acquisition speed and sampling period. Spatial integration of spectra rather than sampling time can also increase certainty in gamma-ray spectra.

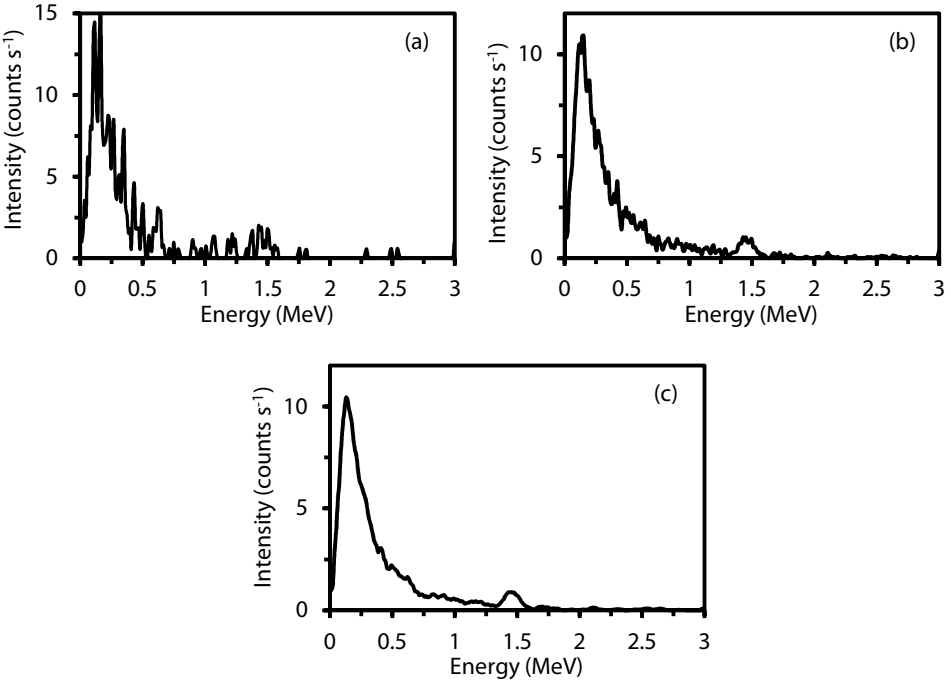

Figure 4.3. *Examples of (a) a raw gamma-ray spectrum measured every second, (b) moving average of seven spatial spectra in a row and (c) moving average of five channels within a spectrum.*

The overall gamma-ray count rate was very low when compared with a typical airborne gamma-ray spectrum reported by Wilford et al. (1997). Very low number of gamma-ray counts in measured spectra is probably due to a sandy loam texture of the fields with leached profile. Overall low number of counts also indicates that the soils are very young because they were reclaimed from the IJsselmeer in the 1960ies. Among the three radionuclides, only ^{40}K showed a prominent peak at 1.46 MeV in the measured spectra, whereas the peaks of ^{238}U and ^{232}Th were very small. A small peak of ^{137}Cs was also noticed around 0.66 MeV. Low number of counts in ^{238}U and ^{232}Th windows indicates that the soil is lacking in ferruginous materials (Dickson and Scott, 1997), whereas a relatively high signal of ^{40}K indicates that the soil is young and rich in K feldspar. Higher energy channels beyond 1.90 MeV collected either very low or zero counts as shown in Figure 4.3(a, b, c). In total radioactivity, the most part of radioactivity is contributed by the ^{40}K and the other two radionuclides contribute the least.

4.4.3. Sensitivities and stripping factors for EWs

Sensitivities and stripping factors or ratios for EWs determined from the standard spectra of the three radionuclides are given in Tables 4.3 and 4.4. Sensitivities of radionuclides removed the effects of other radionuclides in the principal EW of a certain radionuclide, whereas the stripping ratios converted the count rates into elemental activity concentration in Bq kg^{-1}. Sensitivities and stripping factors calculated in this study were different from those determined by IAEA (2003) because these parameters depend on the type of detector used and its geometry.

Table 4.3. *Sensitivities (S) of EWs calculated from the standard spectra of radionuclides*

Radionuclides	Sensitivities (S)		
	EW_{1K} [a]	EW_{2U} [a]	EW_{3Th} [a]
K (^{40}K)	0.0328	0	0
U (^{238}U)	0.0605	0.0658	0.0030
Th (^{232}Th)	0.0483	0.0372	0.0963

[a] Subscrits1, 2 and 3 indicate the number of energy window in sequence on the gamma-ray spectrum

Table 4.4. *Stripping ratios/factors calculated from the sensitivities of the spectrometer (please also consult Table 4.3 for more information)*

Stripping parameters	Ratio of sensitivities (S)	Stripping ratio
α	S_{2Th}/S_{3Th} = 0.0372/0.0963	0.3867
β	S_{1Th}/S_{3Th} = 0.0483/0.0963	0.5018
γ	S_{1U}/S_{2U} = 0.0605/0.0658	0.9193
a	S_{3U}/S_{2U} = 0.0030/0.0605	0.0453
b	S_{3K}/S_{1K} = 0/0.0328	0
g	S_{2K}/S_{1K} = 0/0.0328	0

4.4.4. Correlation between the FSA and the EWs concentrations

Significant linear correlations (Pearson's correlation coefficient, $r > 0.80$) were found between activity concentrations of radionuclides determined by the FSA and the EWs methods. The highest correlation was found for ^{40}K ($r = 0.90$). High correlation between radionuclide concentrations measured by the FSA and the EWs methods indicates that accumulation of gamma rays of each radionuclide in its representative EW represents its distribution in the rest of the energy spectrum. The number of counts in the EWs, therefore, can serve as an indicator to reflect the presence of counts of a specific radionuclide in the entire gamma-ray spectrum. In the FSA method, the main contribution of a radionuclide comes from its respective EW and less from the rest of energy spectrum due to overlapping signals of all radionuclides in the continuum part of the spectrum.

4.4.5. Calibration of radionuclide data

Calibration results of individual and combined fields are shown in Table 4.5. In individual fields, the R^2 values greater than 0.23 were statistically significant at 5 % probability level ($p = 0.05$), whereas the R^2 values greater than 0.35 were statistically significant at 1 % probability level ($p = 0.01$). Similarly in combined fields, relations were significant at 5 % and 1 % probability level when the R^2 values were greater than 0.13 and 0.18, respectively (Table 4.5). Both methods (the FSA and the EWs) established similar correlations with soil properties in the top 0-15 cm and the 15-30 cm soil depths of individual and combined fields. Overall low correlations of radionuclides with soil properties may be attributed to the low number of counts of radionuclides in this study because the number of counts of radionuclides is directly related with the strength of correlations of soil properties (Wong and Harper, 1999). However, the highest number of counts were exhibited by ^{40}K and much fewer by ^{232}Th and ^{238}U. But, most correlations were established between soil properties and ^{232}Th and ^{238}U radionuclides despite of yielding low number of counts (Table 4.5). This may be attributed to the fact that most soil properties are related with ^{232}Th and ^{238}U radionuclides rather than ^{40}K depending on the composition of the soil.

The strength of correlations was mostly higher in the top 0-15 cm depth than the 15-30 cm depth. Similarly, the strength of correlations was higher in the individual fields than when combining them. Trends of correlations in the calibration were almost consistent across methods (FSA and EWs) but were not so consistent across fields. This means that relations between radionuclides and soil properties are site-specific and are likely to depend upon the geochemistry and internal soil processes of a soil. In the top 0-15 cm depth, the FSA method showed a good correlation for clay, pH, TOC and TN in individual fields ($R^2 \geq 0.32$), whereas the EWs method yielded similar correlations for these soil properties in the conventional field, but lower correlations in the organic field. Most soil properties were correlated with ^{232}Th in the top 0-15 cm soil depth and with ^{238}U in the 15-30 cm depth of individual fields. This implies that the signal attenuation in the 15-30 cm depth is more for ^{232}Th compared with ^{238}U. It may also be because ^{238}U is sourced from slightly deeper in the soil profile and also possesses ability to escape the deeper soil layers than the other radionuclides. Clay showed a consistent correlation with ^{232}Th in the top 0-15 cm soil depth in both fields and

methods. Good correlation of clay content with radionuclides data seems direct due to its consistency, whereas correlations of other soil properties with radionuclides may be indirect because they also have good correlations with clay content. For instance, in the top 0-15 cm soil depth in the conventional field, clay is correlated with sand (R^2 = 0.67), pH (R^2 = 0.49) and TN (R^2 = 0.28). A high correlation of clay content with sand is because sand is the mirror image of clay content. Similar correlations of clay were also found with other soil properties in the organic field and in the 15-30 cm soil depths. The highest correlation in combined field was noticed for sand content (R^2 = 0.46) in the EWs method in both depths. It should be noted that correlations between radionuclide data and soil properties were variable across fields but comparatively consistent across methods.

All radionuclides were not positively correlated with soil properties. For example, ^{232}Th showed a positive correlation with clay, pH and TN. The ^{232}U showed a positive correlation with sand and TOC and negative correlation with other soil properties, whereas ^{40}K showed a negative correlation with TOC.

Table 4.5. *Calibration statistics for individual as well as combined fields*

Soil property	Conventional field (*n* = 18 for each depth)				Organic field (*n* = 18 for each depth)				Combined fields (*n* = 36 for each depth)			
	FSA		EWs		FSA		EWs		FSA		EWs	
	RN[a]	R^2	RN	R^2	RN	R^2	RN	R^2	RN	R^2	RN	R^2
0-15 cm soil depth												
Clay (%)	Th	0.50	Th	0.51	Th	0.43	Th	0.60	Th	0.38	Th	0.29
Silt (%)	U	0.21	U	0.18	Th	0.14	Th	0.31	U	0.12	Th	0.35
Sand (%)	Th	0.17	U	0.18	Th	0.22	Th	0.44	Th	0.26	Th	0.46
EC (mS m^{-1})	TC	0.16	TC	0.16	Th	0.22	Th	0.48	U	0.08	Th	0.36
pH	Th	0.47	Th	0.47	Th	0.52	Th	0.59	Th	0.20	K	0.08
TOC (mg g^{-1})	K	0.65	K	0.50	TC	0.32	U	0.10	K&U	0.43	U	0.17
TN (mg g^{-1})	Th	0.33	Th	0.42	K	0.33	K	0.15	K	0.13	K	0.09
15-30 cm soil depth												
Clay (%)	U	0.34	U	0.36	U	0.20	U	0.15	U	0.35	U	0.29
Silt (%)	U	0.34	U	0.36	U	0.11	U	0.11	U	0.37	U	0.39
Sand (%)	U	0.41	U	0.44	U	0.25	U	0.22	U	0.43	U	0.46
EC (mS m^{-1})	U	0.24	U	0.10	Th	0.01	K	0.01	Th	0.02	K	0.01
pH	U	0.35	U	0.23	Th	0.05	Th	0.04	U	0.14	U	0.15
TOC (mg g^{-1})	U	0.16	U	0.17	U	0.11	K	0.07	TC	0.01	TC	0.01
TN (mg g^{-1})	U	0.37	U	0.25	U	0.04	Th	0.01	Th	0.00	TC	0.02

[a]RN stands for radionuclides.

4.4.6. Prediction of soil properties using the FSA method in individual fields

In the conventional field, good correlations were found between measured and predicted clay, pH, TN and TOC ($R^2 \geq 0.45$) in the top 0-15 cm depth (Table 4.6). Contrary to the top 0-15

cm depth, generally lower correlations were found between measured and predicted soil properties in the 15-30 cm soil depth ($R^2 \leq 0.37$). The highest prediction accuracy was shown by pH ($R^2 = 0.37$) in the 15-30 cm depth. In the organic field, clay, sand, pH and TN were significantly predicted ($R^2 \geq 0.35$) in the top 0-15 cm depth. The highest accuracy was found for clay content ($R^2 = 0.73$). In the 15-30 cm soil depth, clay and sand were predicted with a good accuracy ($R^2 \geq 0.52$). A soil property that showed a lower correlation in the calibration was generally predicted with a lower accuracy and vice versa.

Table 4.6. *Statistics of validation/predictions in individual fields using the FSA and the EWs methods*

Soil property	Conventional field (n = 18 for each depth)						Organic field (n = 18 for each depth)					
	FSA			EWs			FSA			EWs		
	R^2	RMSEP	p	R^2	RMSEP	p	R^2	RMSEP	p	R^2	RMSEP	p
0-15 cm soil depth												
Clay (%)	0.65	0.96	0.000	0.59	1.06	0.000	0.73	0.81	0.000	0.67	0.82	0.000
Silt (%)	0.19	2.07	0.068	0.27	2.01	0.028	0.16	3.42	0.105	0.21	3.24	0.056
Sand (%)	0.31	2.90	0.017	0.38	2.83	0.006	0.35	3.67	0.009	0.40	3.36	0.005
EC (mS m^{-1})	0.18	2.25	0.081	0.18	2.25	0.081	0.10	3.95	0.204	0.19	3.89	0.071
pH	0.65	0.01	0.000	0.65	0.01	0.000	0.39	0.05	0.006	0.43	0.05	0.003
TOC (mg g^{-1})	0.45	0.27	0.002	0.47	0.27	0.002	0.17	0.78	0.090	0.34	0.69	0.011
TN (mg g^{-1})	0.56	0.04	0.000	0.75	0.03	0.000	0.41	0.05	0.004	0.28	0.05	0.024
15-30 cm soil depth												
Clay (%)	0.13	1.52	0.134	0.11	1.58	0.186	0.55	0.57	0.000	0.62	0.55	0.000
Silt (%)	0.30	2.33	0.020	0.42	2.13	0.004	0.22	0.91	0.051	0.18	0.93	0.079
Sand (%)	0.28	3.34	0.023	0.35	3.18	0.010	0.52	1.09	0.001	0.51	1.12	0.001
EC (mS m^{-1})	0.05	2.90	0.396	0.11	2.74	0.177	0.04	1.94	0.403	0.05	2.01	0.360
pH	0.37	0.04	0.007	0.41	0.04	0.004	0.34	0.02	0.012	0.28	0.02	0.025
TOC (mg g^{-1})	0.03	0.56	0.463	0.07	0.54	0.294	0.09	0.17	0.240	0.08	0.20	0.247
TN (mg g^{-1})	0.26	0.15	0.032	0.26	0.14	0.030	0.11	0.06	0.169	0.15	0.06	0.110

4.4.7. Prediction of soil properties using the EWs method in individual fields

Prediction accuracies of soil properties in the EWs method were comparable with the FSA method, however, slightly better prediction were found for a few soil properties (Table 4.6). In the conventional field, clay, sand, pH, TOC and TN were significantly predicted ($R^2 \geq 0.38$) in the top 0-15 cm soil depth. The highest accuracy was obtained for TN ($R^2 = 0.75$). In the 15-30 cm soil depth, silt, sand and pH were predicted with good correlations ($R^2 \geq 0.35$) and TN showed significant but a lower accuracy ($R^2 \geq 0.26$). In the organic field, clay, sand, pH, TOC and TN were predicted significantly ($R^2 \geq 0.28$) in the top 0-15 cm soil depth, whereas in the 15-30 cm depth, clay, sand and pH were significantly predicted ($R^2 \geq 0.28$). Clay showed good prediction accuracy in both depths ($R^2 \geq 0.62$). Higher prediction accuracies were found for those soil properties that showed higher correlations in the calibration.

4.4.8. Prediction of soil properties in combined fields

When both fields were combined, the accuracy of predictions of soil properties was comparable in both methods, but decreased as compared with the individual fields (Table 4.7). The highest prediction accuracy was found for clay content (R^2 = 0.63) in the FSA method in the top 0-15 cm depth. All other soil properties were predicted with lower accuracies in both methods and depths ($R^2 \leq 0.42$).

4.4.9. Comparison between the FSA and the EWs methods

Accuracies of prediction of soil properties in the FSA and EWS methods were comparable and both methods can be used to find relationships with soil properties. The EWs method, however, yielded slightly better results than the FSA method for a few soil properties, which is unexpected. Slightly lower accuracy of predictions in the FSA method may be attributed to the uncertainties in deriving radionuclide activity concentrations caused by the covariance between the standard spectra of radionuclides, which are increased compared with the EWs method. The increased covariance is caused by the inclusion of the Compton part of the gamma-ray spectrum for ^{238}U and ^{232}Th, since their spectra are most similar in the continuum part (Hendriks et al., 2001). This is the drawback of this FSA method. Although the FSA method is advantageous that accounts for the entire gamma-ray spectrum in gamma-ray spectroscopy, the EWs method can also establish accurate relations between radionuclides and soil properties. The FSA method used in this study is faster than the EWs method and can convert raw spectra into elemental concentrations based on the standard spectra of radionuclides. The EWs is a simple and relatively easy method when sensitivities and stripping factors of the spectrometer are known.

Better predictions were found in individual fields than when combining them. Low accuracy of predictions in combined fields is attributed to different radionuclides correlating a specific soil property in both fields during calibration. For example, in the top 0-15 cm depth for both methods, TN was correlated with ^{232}Th in the conventional field, whereas it was correlated with ^{40}K in the organic field (Table 4.5). Combining fields, TN yielded a lower correlation with ^{40}K for both methods those results in lower prediction accuracy. Similarly, other soil properties lose their accuracy in combined fields. Results of diminished accuracies in combined fields are consistent with those of Van der Klooster et al. (2011), who found better prediction accuracies in field-scale studies.

4.4.10. Prediction accuracies in the top 0-15 cm and 15-30 cm soil depths

Lower prediction accuracies of soil properties in the 15-30 cm depth imply that the proportion of detected gamma-ray signal decreases with increasing soil depth or thickness. Increasing bulk density further attenuates the gamma-ray signal and reduces the gamma-ray emission (Taylor et al., 2002). Signal attenuation prevents the accurate determination of soil properties from the 15-30 cm soil depth because fewer number of gamma-ray counts are escaped the soil matrix from the deeper soil layers. Attenuation of gamma rays from deeper

soil depths may be even more when a low number of gamma rays, as in this study, is emitted by the soil. Low correlation of radionuclides with the soil properties of the 15-30 cm depth is also because they were not correlated with those of the top 0-15 cm depth. This is consistent with the results from Viscarra Rossel et al. (2007). Taylor et al. (2002) reported that correlation between radionuclides and soil properties at 10 cm interval down to 30 cm decreases with increasing soil depth. Fifty per cent of the observed spectra originates from the top 10 cm soil and 90 % originates from the top 30 cm.

Table 4.7. *Statistics of validation/predictions for combined fields using the FSA and the EWs methods*

Properties	0-15 cm soil depth (n = 36)						15-30 cm soil depth (n = 36)					
	FSA			EWs			FSA			EWs		
	R^2	RMSEP	p	R^2	RMSEP	p	R^2	RMSEP	p	R^2	RMSEP	p
Clay (%)	0.63	1.00	0.000	0.40	1.25	0.000	0.18	1.13	0.009	0.19	1.17	0.007
Silt (%)	0.06	3.67	0.145	0.16	3.60	0.014	0.29	2.29	0.001	0.27	2.39	0.001
Sand (%)	0.25	3.77	0.002	0.33	3.61	0.000	0.33	2.84	0.000	0.31	3.01	0.000
EC (mS m^{-1})	0.13	3.95	0.028	0.15	4.24	0.019	0.06	2.90	0.156	0.05	2.82	0.184
pH	0.24	0.05	0.003	0.08	0.05	0.080	0.14	0.03	0.027	0.15	0.03	0.019
TOC (mg g^{-1})	0.42	0.54	0.000	0.32	0.59	0.000	0.08	0.43	0.096	0.08	0.43	0.096
TN (mg g^{-1})	0.30	0.06	0.001	0.19	0.06	0.008	0.11	0.12	0.053	0.04	0.12	0.224

Results suggest that gamma-ray spectroscopy can generally benefit soil characterisation for annual crops where the condition of the seedbed is important because the method is restricted to near surface soil sensing. The benefits of the method can be extended to perennial crops when subsurface soil properties are correlated with the surface soil properties.

4.4.11. Prediction of soil properties based on RPD statistic

In bivariate data analysis, such as simple correlation and linear regression, the significance of models is normally tested by the R^2, standard error of estimate or RMSEP and F-test values. In contrast, when hyper-spectral data of sensors (i.e. gamma-ray data) are combined with multivariate calibration methods, the predictability or significance of models is hardly tested using F-statistics because the number of predictor variables is mostly higher than the number of observations. Therefore, the predictability of a model is tested using R^2, RMSEP and ratio of per cent deviation (RPD) statistics (Viscarra Rossel et al., 2007). In this study, we attempt to use F-statistics and RPD values to compare the models. With the new developments in statistical and mathematical techniques, the appropriate statistical parameters can be chosen for assessment of different prediction models based on the type of method used for analysis.

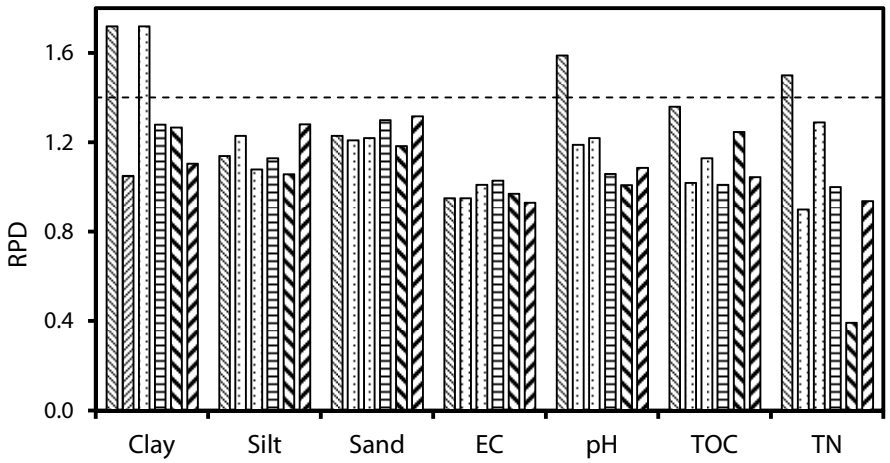

Figure 4.4. *RPD statistic of individual and combined fields in 0-15 cm and 15-30 cm depths for the FSA method. Legend: = conventional field 0-15 cm depth, = conventional field 15-30 cm depth, = organic field 0-15 cm depth, = organic field 15-30 cm depth, = combined fields 0-15 cm depth and = combined fields 15-30 cm depth. Dashed line indicates the RPD value of 1.4, which is a threshold commonly used in chemometrics.*

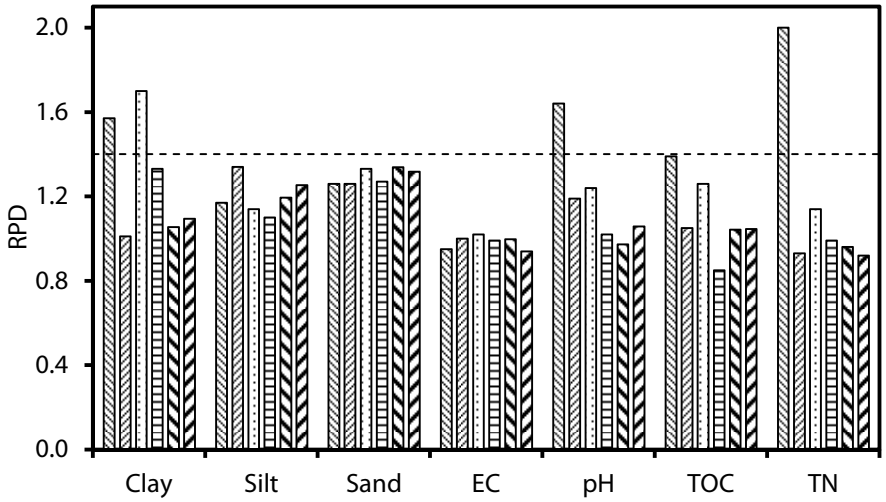

Figure 4.5. *RPD statistic of individual and combined fields in 0-15 cm and 15-30 cm depths for the EWs method. Legend: = conventional field 0-15 cm depth, = conventional field 15-30 cm depth, = organic field 0-15 cm depth, = organic field 15-30 cm depth, = combined fields 0-15 cm depth and = combined fields 15-30 cm depth. Dashed line indicates the RPD value of 1.4, which is a threshold commonly used in chemometrics.*

The RPD values of predicted soil properties were mostly higher in the top 0-15 cm soil depths and lower in the 15-30 cm depths for individual and combined fields (Figures 4.4 and 4.5), which are consistent with the F-statistics and R^2 values listed in Tables 4.6 and 4.7. Clay content showed RPD values greater than 1.4 (a threshold that is widely used in chemometrics) in the 0-15 cm soil depth for both fields and methods. The highest RPD value was obtained for TN (2.0) in the EWs method in the 0-15 cm depth of the conventional field. Soil pH and TN also showed RPD > 1.4 in the conventional field for both methods. Based on the RPD values we can suggest that clay, pH and TN can be predicted successfully using gamma-ray spectroscopy when combined with either the FSA or the EWs data analysis method. Other soil properties showed lower RPD values in individual fields. When combining fields, generally lower RPD values were obtained.

4.4.12. Gamma-ray spectroscopy and soil characterisation

Results from this study indicate that relationships exist between certain soil properties and radionuclide data, which suggest a potential role of gamma-ray spectroscopy in soil property mapping. The relationship between ^{232}Th and clay content in surface soil depths indicates that clay content can be measured by measuring ^{232}Th signal. Correlation between ^{232}Th and clay, pH and TN were consistent across fields and methods. Results of correlations between ^{232}Th and clay content are consistent with those of Cook et al. (1996), Pracilio et al. (2006), Van Egmond et al. (2010) and Van der Klooster et al. (2011), but are not consistent with those of Taylor et al. (2002), who correlated TC with clay content. We did not find TC significantly correlating with any soil property in any field and method. The TC can be used to relate clay content if other radionuclides also correlate with clay content. The ^{40}K was least correlated with soil properties. Both the FSA and the EWs methods elucidate that clay content appears to have a direct relationship with radiometric data, whereas good correlations between radiometric data and other soil properties, such as sand, pH and TN, may be due to their correlations with clay content.

The influence of different field management systems on soil property prediction was also studied. Soil property predictions were not so consistent across fields, but the soil properties of both fields showed similar statistics. This difference may be due to the management, as in one field the fertilisers were added. However, there is no evidence in literature that fertilisers can affect the gamma-ray emission from soil.

4.5. Conclusions

We demonstrated the usefulness of gamma-ray spectroscopy to predict soil properties using the EWs and the FSA methods.

Radionuclide concentrations determined by the EWs and the FSA methods show good correlations with each other meaning that the number of counts of a radionuclide in its EW reflects the number of counts elsewhere in the spectrum.

Both methods yield comparable predictions when regressed against soil properties. In the conventional field, clay, pH and TN are predicted with a good accuracy in the top 0-15 cm soil depth in both methods, whereas in the organic field, this is only so with clay. The highest prediction accuracy is found for TN in the conventional field when combined with the EWs method.

Prediction accuracies of soil properties are higher in the individual fields than when combining them and thus calibration at field level is required. Only clay content is predicted in combined fields with a good accuracy in both methods.

Good prediction accuracy for clay content in both methods and fields leads us towards the conclusion that clay content appears to have a direct relationship with radiometric data, whereas the good correlations with other soil properties, such as sand, pH and TN may be due to their correlations with clay content.

Good prediction results suggest a potential role of gamma-ray spectroscopy in modelling and mapping soil properties. Soil properties in the top 0-15 cm soil depths are predicted better than in the 15-30 cm soil depths. This implies that gamma-ray spectroscopy can generally benefit soil characterisation for annual crops where the condition of the surface layer and seedbed is important. The method is not suited for determining small differences in structure resulting from management.

As for the methodology, from the findings of this study we conclude that the EWs method can establish relations between radionuclide data and soil properties as accurate as the FSA method.

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Chapter 5

Sensor data fusion to predict multiple soil properties

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5.1. Abstract

The accuracy of a single sensor is often low because all proximal soil sensors respond to more than one soil property of interest. Sensor data fusion can potentially overcome this inability of a single sensor and can best extract useful and complementary information from multiple sensors or sources. In this study, a data fusion was performed of a vis-NIR spectrometer and an EM38 sensor for multiple soil properties. Stepwise multiple linear regression (SMLR), partial least squares regression (PLSR) and principal components analysis combined with stepwise multiple linear regression (PCA+SMLR) methods were used in three different fields. Soil properties investigated for data fusion included soil texture (clay, silt and sand), EC, pH, total organic carbon (TOC), total nitrogen (TN) and carbon to nitrogen ratio (CN). It was found that soil property models based on fusion methods significantly improved the accuracy of predictions of soil properties measureable by both sensors, such as clay, silt, sand, EC and pH from those based on either of the individual sensors. The accuracy of predictions of TOC, TN and CN was also improved in some cases, but was not consistent in all fields. Among data fusion methods, PLSR outperformed both SMLR and PCA+SMLR methods because it proved to have a better ability to deal with the multi-collinearity among the predictor variables of both sensors. The best data fusion results were found in a clayey field and the worst in a sandy field. It is concluded that sensor data fusion can enhance the quality of soil sensing in precision agriculture once a proper set of sensors has been selected for fusion to estimate desired soil properties. More efficient statistical data analysis methods are needed to handle a large volume of data effectively from multiple sensors for sensor data fusion.

Keywords: soil properties; vis-NIR spectrometer; EM38, sensor data fusion; statistical methods for fusion.

5.2. Introduction

Characterisation of spatial variability of soil physical and chemical properties within a field is unavoidable within the precision farming paradigm (McBratney and Pringle, 1997). The economic consideration in conventional soil sampling and laboratory analysis results in low sampling density that is insufficient to characterise the landscape variability accurately. Attempts are being made to complement or even replace the conventional methods with more efficient and cost effective methods. Different soil sensors can scan soils with spatially dense measurements, although their outcome is not as accurate as that of laboratory methods. To capture fine-scale variations in soil properties, lots of cheap and imprecise measurements might be even more effective than a few expensive precise ones (Minasny and McBratney, 2002).

Advances in remote and proximal soil sensing methods have made it possible to acquire large volumes of soil and crop data rapidly for efficient and effective resource management. Kuang et al. (2012) presented a comprehensive review of different soil sensing methods used in laboratory, in-situ and on-line and evaluated their performance to characterise different soil properties. Two types of soil sensing methods are common in precision agriculture: reactive and predictive. A reactive (real-time) sensor changes the rate of application of an input in response to local conditions at the time of application. In contrast, a predictive (map-based) sensor acquires the data and generates soil property maps off-site after processing and interpreting the data followed by decision-making about the optimal use of agricultural inputs (Adamchuk et al., 2011). The reactive methods do not have widespread feasibility due to their complexity of design and seem less optimal if the spatial distribution of a sensed soil property (e.g. apparent soil electrical conductivity) does not change during the growing season. The predictive methods have more widespread utility in precision agricultural applications. Here, a predictive approach was focussed on.

The accuracy of a single sensor is often low because all proximal soil sensors respond to more than one soil property of interest (Adamchuk et al., 2011; Kuang et al., 2012). Due to the complex nature of agricultural soils, a sensing technique that provides information about one soil parameter is considered of limited use when certain environmental and soil constraints, such as rainfall, other types of precipitations, soil temperature, soil particle size and many others disturb the output of single sensor systems. This makes the interpretation of corresponding relationships between sensor output and a soil property more complex and uncertain (Mahmood et al., 2009). The inability of single-sensor based systems can be overcome by combining conceptually different sensing methods and integrating the subsequent data that holds promise for providing complementary and more robust soil property estimates and leads to increased adoptability of sensor-based crop management (Adamchuk et al., 2011; Mahmood et al., 2009).

Data fusion or data integration is an important tool that may improve the performance of a detecting system when various complementary sensors are available. The aim of a data fusion approach is to obtain target information with better quality and reliability (Mahmood et al., 2009). Data fusion may perform inferences that are potentially more accurate than if they were achieved by a single sensor. In multi-sensor remote sensing applications, a data

fusion approach can be applied to confirm the decision derived from a single sensor data and to analyse complementary information about the same observed property for soil sensing (Park et al., 2002).

To realise the effectiveness of sensor data fusion, a few preliminary attempts have been made for complementary data fusion. Wong et al. (2010) used a dual EM38-gamma-ray soil sensing approach with a rule-base method and overcame the inability of a single sensor to successfully predict topsoil depth and soil pH. Taylor et al. (2010) made an attempt towards data fusion using a gamma-ray spectrometer and an EM38 sensor to predict topsoil clay content. The authors concluded that the soil property models based on both sensors predicted topsoil clay content better than models based on either of the sensors. Piikki et al. (2011) attempted to combine the data of a gamma-ray spectrometer and an EM38 with addition of other ancillary data, such as elevation, radiance and drainage data, to map topsoil clay content. Although both sensors could not add to a significant improvement in the quality of clay prediction, the ancillary data helped to produce better results. Schirrmann et al. (2011) evaluated a sensor fusion system comprising a pH sensor, a vis-NIR spectrometer and an EC_a sensor for mapping soil macronutrients. The authors concluded that only the prediction of pH was improved by combining the data from all three sensors. This literature review showed that there is potential to get better soil property estimates using sensor data fusion, although this approach has not been extensively tested for predicting multiple soil properties.

Sensor data fusion may provide many possible benefits, such as robust accuracy, extended attribute coverage and complementary information on certain soil properties (Mahmood et al., 2009). Nevertheless, very limited and non-refereed research has been done on this topic that can be taken as reference for complementary sensor data fusion in the framework of precision agriculture. Furthermore, as data fusion is a new field of research, literature so far has not provided clues about the best statistical and geostatistical data handling and analysis methods for sensor data fusion to get the maximum benefit from this approach.

In this study, it was hypothesised that the sensor data fusion technique can best extract useful information from a vis-NIR spectrometer and an EM38 sensor and will improve the accuracy of predictions of measureable soil properties by both sensors compared to either of the individual sensors. The objective of the study was to perform data fusion of a vis-NIR spectrometer and an EM38 sensor to predict several soil properties and to compare the accuracy of predictions with that of either of the individual sensors. These two sensors were used for fusion because they encapsulate a large proportion of literature on precision agriculture and proximal soil sensing. Furthermore, the ability of stepwise multiple linear regression (SMLR), partial least squares regression (PLSR) and principal components analysis (PCA) combined with SMLR was compared to identify the most suitable statistical method for performing data fusion. Soil properties of interest were soil texture (percentages of clay, silt and sand fractions), soil electrical conductivity (EC), pH, total organic carbon (TOC), total nitrogen (TN) and carbon to nitrogen ratio (CN).

5.3. Materials and methods

5.3.1. Description of study fields

Three fields with different texture were selected in the Netherlands for this study in the neighbourhood of Wageningen and Lelystad.

Field 1 was located in the west of Wageningen (51°57'37.45"N, 5°38'35.96"E). The area of the field was about 4 ha. Soil texture was silty clay loam with approximately 37 % clay. The field was planted with summer wheat and measurements were carried out after the harvest in October-November 2010.

Field 2 was located in the north of Wageningen (51°59'23.63"N, 5°39'37.05"E). The area of the field was about 1 ha. The texture of the field was sandy with airborne deposited sand. Soil of this field had a very low clay content (5 %). Below the plough layer, decomposed oxides of iron were found. The field was planted with maize and measurements were carried out after the harvest in October 2010.

Field 3 was located at the experimental farm of Wageningen University, the "Broekemahoeve", near Lelystad (52°32'35.67"N, 5°34'26.50"E). The area of the field was about 4 ha. Soil texture of the field was sandy loam with varying amounts of small stones and seashells. Mean clay content was 19 %. The field was planted with onion and measurements were carried out in the growing crop in June 2010.

5.3.2. Soil sampling

Soil samples were collected from the 0-0.30 m top soil layer from Fields 1 and 2. From Field 3, samples from two depths were taken: 0-0.15 m and 0.15-0.30 m. A total of 189 soil samples were collected from three fields. Soil samples were collected either using a regular grid of 11 m x 11 m (Field 1) or following transects of regular intervals ranging from 15 to 30 m (Fields 2 and 3). The number of samples taken was 77, 24 and 88 from Field 1 through 3, respectively depending on the area of the field and the measurement grid/transect. A 40-mm diameter stainless steel core was used to take soil samples. Soil samples from each location were taken within a diameter of one metre from the central grid point to take into account soil volume sensed by the EM38. Usually, a single soil core is taken from about 1.20 m depth to incorporate the effective sensed depth by EM38 assuming that the soil is uniform laterally at the sampling node (Sudduth et al., 2005). In this study, the lateral sensed area by EM38 was considered up to 0.30 m depth assuming a homogeneous soil profile down to the effective measurement depth of EM38. Typically 5-8 soil sampling cores were taken and composited per location to make enough volume of sample. These composited samples were air dried in an oven at 40 °C for 72 hours and sieved in the lab with a 2-mm mesh. Samples were divided into two subsets: one for spectral measurements in the laboratory and the other for laboratory soil analysis.

5.3.3. Apparent soil electrical conductivity (ECa) measurement

Apparent soil electrical conductivity (EC_a) was measured using a handheld EM38 (Geonics Ltd, Mississauga, ON, Canada), which uses an electromagnetic induction principle. When the instrument is placed in the vertical coil configuration, the effective exploration depth is about 1.5 m and in the horizontal coil configuration, the effective depth of the measurement is 0.75 m (McNeill, 1980). The effective depth of exploration is regarded as the measurement of about 70 % relative sensitivity of the EM38. In vertical dipole mode, the strongest response comes from the deep soil, whereas in the horizontal mode, the surface soil contributes the most to EC_a (McNeill, 1980). From each sampling location, soil EC_a was measured in both horizontal ($EC_{a\text{-}H}$) and vertical ($EC_{a\text{-}V}$) dipole modes. The EM38 was nulled and calibrated before using in each field. Two to three measurements were taken in each dipole mode in the neighbourhood of the sampling point to incorporate possible variation within the one meter sample diameter. The mean of three EC_a measurements was subsequently calculated in each mode to get representative measurements from each sampling location. Changes in ambient conditions, such as air temperature, humidity and atmospheric electricity (lightning) can influence the EC_a values, therefore, the EC_a measurement and soil sampling from each field were done on the same day. Soil temperature was also measured at each sampling location (three replications) using a thermocouple sensor in the top 0.30 m depth to correct EC_a measurements for temperature effects (McNeill, 1980). The EC_a measurements were then standardised to a temperature of 25 °C using the equation suggested by Slavich and Petterson (1990).

5.3.4. Spectral measurement

Soil reflectance was measured using a portable ASD FieldSpec® vis-NIR spectrometer (Analytical Spectral Devices, Inc., Boulder, Colorado, USA) with a spectral range of 350-2500 nm. In-situ measurement of vis-NIR reflectance can scan only the top few millimetres of soil and measuring reflectance from one metre diameter from 0-0.30 m soil depth was difficult. This could be done ex-situ by taking soil cores from the intended depth and measuring vis-NIR reflectance from the length of the cores. Nevertheless, avoiding the effects of interfering factors, such as moisture content, particle size, roots, debris and stones was not possible. Therefore, in this study, the vis-NIR reflectance spectra were measured in the laboratory, although this involved some level of pre-treatment of samples. About 20 g of soil from each sample was put in a plastic dish (20 mm deep and 40 mm in diameter). Soil samples were scanned using an ASD contact probe. At the beginning of each spectral measurement session, the instrument was optimised and calibrated by measuring a dark current followed by a white reference measurement using a white Spectralon® reference panel. The instrument was recalibrated after every 10 samples. Soil spectra were collected at 1-nm spectral resolution, yielding a total of 2151 data points (wavenumbers) per spectrum. Each reflectance measurement was the mean of 50 scans to minimise noise. Three measurements were obtained for each sample placing the contact probe at a slightly different location each time.

5.3.5. Laboratory analysis of soil physical and chemical properties

All samples were subjected for determination of soil texture, soil electrical conductivity in water solution (EC), soil pH, total organic carbon (TOC) and total nitrogen (TN). The carbon to nitrogen ratio (CN) was also calculated because it influences the rate of decomposition of organic matter that results in mineralisation or immobilisation of soil nitrogen. Fractions of sand, silt and clay content were determined using the hydrometer method (Soil Survey Staff, 2009). Soil $EC_{1:1}$ and soil $pH_{1:1}$ were determined using an Eijkelkamp® 18.28 Multi Parameter Analyser with EC and pH probes. Soil solution of 1:1 (soil: deionised water) ratio were prepared for determination of both $EC_{1:1}$ and $pH_{1:1}$ as described by Soil Survey Staff (2009). Total organic carbon (TOC) was determined by sulfochromic oxidation according to ISO-14235 soil quality standard. Total nitrogen (TN) was determined from the sum of N-Kjeldahl, $N\text{-}NO_3^-$, $N\text{-}NO_2^-$, $N\text{-}NH_3^+$ and N-organic after UV digestion.

5.3.6. Spectral preparation, processing and data analysis

Spectral data of individual fields were imported in SAMS (Spectral Analysis and Management System, University of California, Davis) software. The mean was calculated of three spectral measurements from each sample. Soil spectra were then subjected for partial least squares regression (PLSR) using ParLeS (PLSR software, University of Sydney, Australia) software (Viscarra Rossel, 2008). Different processing options, such as transformation of reflectance to absorption, baseline correction, derivative analysis and mean centring were attempted; only mean centring helped to improve the analysis because spectra were not noisy due to lab conditions. Spectra were, therefore, mean-centred before performing further analysis.

Spectral data of individual fields were imported in SAMS (Spectral Analysis and Management System, University of California, Davis, USA) software. The mean was calculated of three spectral measurements from each sample. Soil spectra were then subjected to partial least squares regression (PLSR) using ParLeS (PLSR software, University of Sydney, Australia) software (Viscarra Rossel, 2008). Different processing options, such as transformation of reflectance to absorption (to reduce noise and non-linearities), baseline correction (to normalise the spectra for improving the robustness of PLSR models), derivative analysis (to eliminate background effects and enhance spectral resolution) and mean centring (to enhance the subtle differences between spectra by shifting the data towards the mean) were attempted (Viscarra Rossel, 2008); only mean centring helped to improve the analysis because spectra were not noisy due to lab conditions. Spectra were, therefore, mean centred before performing further analysis.

5.3.7. ECa data analysis

Soil properties were regressed to EC_a measurements taken in horizontal and vertical dipoles ($EC_{a\text{-}H}$ and $EC_{a\text{-}V}$) using stepwise multiple linear regression (SMLR). Both $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$ measurements were used as predictor variables and soil properties as the response variables. The data were analysed using PASW statistical software (PASW, Inc., Chicago IL, USA).

5.3.8. Data fusion

Three types of statistical methods were used for data fusion: stepwise multiple linear regression (SMLR), partial least squares regression (PLSR) and principal components analysis combined with stepwise multiple linear regression (PCA+SMLR). The accuracy of predictions using data fusion methods was compared with those of individual sensors and also among these data fusion methods.

5.3.8.1. Multiple linear regression (MLR)

Multiple linear regression (MLR) is the most widely used method to establish relationships between one single dependent and a small number of independent variables. In stepwise multiple linear regression (SMLR), variables are entered one by one in the model. In the final model, only those variables are retained that significantly explain variance in the response variable. Relationships between the response (i.e. dependent) and the predictor (i.e. independent) variables are measured with standardised regression coefficients and are interpreted as partial effects influencing the variability in the response variable (Carrascal et al., 2009; Rawlings et al., 1998).

Robust identification of a few wavebands or wavelengths from spectral data (2151 wavelengths) for SMLR analysis is a difficult task, when hundreds of redundant wavebands have similar correlation with a certain soil property. The variable selection can be done in a number of ways and no method is perfect because they have their own pros and cons. Derivative analysis was performed on spectral data for wavelength (variable or feature) selection that has been previously applied to identify wavebands for estimation of several soil properties (Brown et al., 2005; Kariuki et al., 2004; Melendez-Pastor et al., 2008). Derivatives perform a baseline correction and enhance weak features of chemically relevant peaks in spectra (Duckworth, 1998). Only the first derivative of the reflectance spectra was used (Figure 5.1) that indicates the slope of the spectral curve at every point (Duckworth, 1998). The first derivative of reflectance was computed by taking the difference in reflectance between the reflectance for band number $n + 1$ and band number n and dividing it by the difference of wavelength for the band $n + 1$ and n, as shown in Equation 5.1:

$$R' = \frac{(R_{n+1} - R_n}{(\lambda_{n+1} - \lambda_n)} \qquad \textit{Equation 5.1}$$

where, R' is the first derivative of reflectance R, n is the band number (n = 350, 351, ... 2500) and λ is the wavelength (nm). Ten wavelengths surrounding each peak or dip from vis-NIR spectra were selected and were introduced into PASW software (PASW statistics version 18.0.3) and SMLR analysis was undertaken to find the most significant wavelengths for each soil property. These selected wavelengths together with $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$ were then used as predictor variables and soil properties as the response variables to perform SMLR fusion.

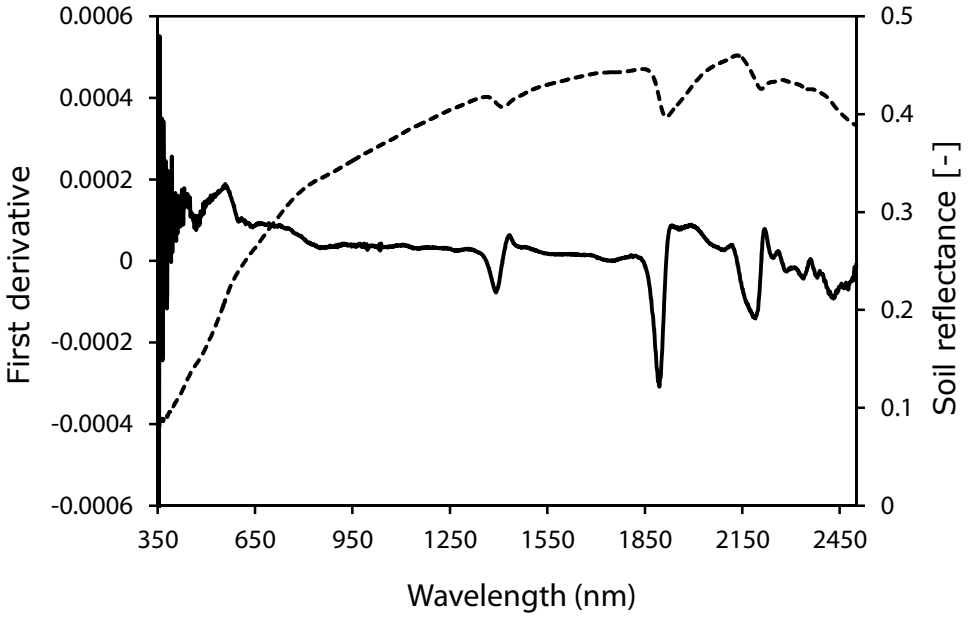

Figure 5.1. *First derivative of the mean reflectance spectrum enhancing the absorption features shown on primary y-axis (solid line). The mean reflectance spectrum (dotted line) is shown on secondary y-axis, indicating the major absorption dips.*

5.3.8.2. Partial least squares regression (PLSR) method

Partial least squares regression (PLSR) is an extension of MLR in which effects of linear combinations of several predictor variables on a response variable or several response variables are analysed. Associations are established with latent factors extracted from predictor variables that maximise the explained variance in the dependent variables. These latent factors are defined as the linear combinations constructed between predictor and response variables, such that the original multi-dimensionality is reduced to detect the structure in the relationships between predictor variables and between these latent factors and the response variables (Carrascal et al., 2009; Hubert and Vanden Branden, 2003). The PLSR is particularly well suited when a large array of independent and highly correlated variables is to be analysed and the sample size is also very small as compared with the number of independent variables.

For sensor fusion using PLSR, both $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$ measurements were also used as predictor variables together with spectral wavelengths. All predictor variables were standardised to zero mean and unit variance (from each data value, the mean of that predictor variable is subtracted and then the result is divided by the standard deviation of that predictor variable) before subjecting to PLSR. Standardisation of predictor variables produced better results compared with the original predictor variables. The best model for prediction was chosen based on leave-one-out cross validation parameters, using the highest R^2 value and the lowest RMSE and Akaike information criterion (AIC) values (Akaike, 1973). The best models thus obtained were used for prediction in validation datasets.

5.3.8.3. Principal components analysis (PCA) combined with SMLR

Principal components analysis (PCA) is also a multivariate data reduction technique that can reduce the multi-dimensionality in the predictor variables without sacrificing much information in the data. PCA was carried out to compress the spectra into fewer principal components (PCs) using R software (R Development Core Team, 2011) and their scores were used as predictor variables in the analysis. The PCA breaks apart the original matrix of spectra or explanatory variables **X** into a score matrix **S** and a loading matrix **L** as shown in Equation 5.2:

$$\mathbf{X}(n \times p) = \mathbf{S}(n \times f)\ .\ \mathbf{L}(f \times p) \qquad \textit{Equation 5.2}$$

where, *n* is the number of observations or spectra, *p* is the number of predictor variables (here 2151 wavelengths) and *f* is the number of PCs or factors. A maximum of 10 PCs were used for the SMLR analysis, although most variation (~ 99 %) in soil spectra was explained by the first two PCs. Next, scores of these PCs and both $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$ measurements were combined with the SMLR to establish relationships between predictor variables (PCA scores and EC_a measurements) and soil properties.

5.3.9. Statistical modelling and comparison of methods

In each field, soil samples were randomly divided into two subsets: calibration and validation. Two-thirds of the samples were used for calibration and the remaining one-third samples were used for validation to test the developed models. The quality of predictions was assessed from the validation subset of the samples. Three replications of calibration and validation samples were obtained randomly for fusion methods from each field. The same configurations of calibration and validation subsets in each replication were used for the EM38 sensor, vis-NIR spectrometer and for data fusion methods in each field. The performance of individual and data fusion methods to predict soil properties was assessed using coefficient of determination (R^2), root-mean squared error of prediction (RMSEP) and ratio of per cent deviation (RPD). Means of statistics of three replications were calculated. The means of R^2 values were compared with those of the individual sensors using independent sample t-test to test if the accuracy of predictions by combining methods was statistically significantly improved.

5.4. Results and discussion

5.4.1. Basic statistics of soil properties

A summary of the basic statistics of soil properties of the three fields is shown in Table 5.1. Soil EC, pH and TOC were similar in Fields 1 and 3, but different from Field 2. The ranges of soil properties in Field 1 were wider than those in Fields 2 and 3. The lower value of EC in Field 2 was due to a lower clay content. A lower value of pH in this field also corresponded to the sandy texture. Because of the aeolian origin, the sands contain sodium and decomposed iron oxides below the plough layer. Distributions of all soil properties were symmetric ($-1 \leq$ skewness ≤ 1) for Fields 2 and 3, however, were not symmetric for clay, silt, TOC and CN in

Field 1. These values were log-transformed and data fusion was performed, but results were not improved. Therefore, these soil properties were used in original form.

Table 5.1. *Values and basic statistics of measured soil properties used for both calibration and validation subsets*

Soil property	Field 1 (silty clay loam) (n = 77)					Field 2 (sandy) (n = 24)					Field 3 (sandy loam) (n = 88)				
	Min	Max	Mean	SD	Skew	Min	Max	Mean	SD	Skew	Min	Max	Mean	SD	Skew
Clay (%)	25.0	42.0	36.9	4.1	-1.5	4.0	6.0	5.0	0.7	0.2	15.0	23.6	18.8	1.8	0.4
Silt (%)	41.0	57.2	52.6	3.6	-1.2	3.5	17.0	9.2	3.8	0.4	15.0	32.8	22.2	4.4	0.8
Sand (%)	3.9	32.0	12.8	6.3	1.1	78.0	92.0	85.8	3.7	-0.5	44.4	68.0	59.0	5.3	-0.6
EC (mS m^{-1})	19.0	45.3	32.3	6.1	-0.5	8.6	14.4	11.5	1.9	0.1	22.4	45.0	33.6	6.4	0.2
pH	6.9	7.7	7.3	0.2	-0.7	5.1	6.2	5.6	0.3	0.3	7.5	8.0	7.7	0.1	0.3
TOC (mg g^{-1})	9.5	17.0	11.5	1.7	1.5	11.1	18.7	15.8	2.0	-0.4	8.6	12.7	10.8	1.1	0.0
TN (mg g^{-1})	1.2	2.0	1.7	0.2	-0.5	0.9	1.4	1.1	0.1	0.5	1.0	1.6	1.3	0.1	0.2
C:N	5.6	10.5	6.8	1.1	1.5	10.9	16.7	14.2	1.6	-0.1	6.1	11.0	8.5	1.1	0.6

5.4.2. Selection of variables from vis-NIR spectra

The selected predictor variables (wavelengths) of vis-NIR reflectance spectra used in the analysis for SMLR are shown in Table 5.2.

Table 5.2. *Selected wavelengths from vis-NIR spectra for using in SMLR analysis*

Soil property	Selected wavelengths (variables)		
	Field 1	Field 2	Field 3
Clay	432, 2500, 1968, 389	351	354, 371, 2452, 2430
Silt	617, 388, 376, 350, 393, 1590, 2498	687	534, 422, 380, 371
Sand	590, 547, 460, 390	693	1935, 354, 370
EC	639, 396, 2422, 2420	904	350, 372, 361, 367
pH	2428	1143	359, 351, 368, 389, 981
TOC	778, 388	653	350, 372, 412
TN	393, 2345, 2326, 2387	733	369, 371, 357
CN	377, 388, 361	355	406, 351, 439, 476, 497, 430

A few wavelengths sometimes produced comparable results with the other data fusion methods, such as PLSR (e.g. clay, silt and sand in Field 1). Different wavelengths were selected by SMLR in three fields depending on differences in soil properties (Table 5.2). Selected wavelengths were also different from those reported in the literature. For example, clay content has a peak around 2300 nm (Clark, 1999), but no field showed wavelengths close to 2300 correlating with clay content. The wavelength closest to 2300 was 2430 in Field 3. Similarly, TOC can also have a similar absorption band around 2300 nm, but most wavelengths correlating with TOC were found to belong to the visible part of the spectrum in the three fields (Table 5.2). It means that different fields have different spectral characteristics for correlating with a certain soil property. Table 5.2 shows that most spectra used in SMLR

belong to the visible region (350-700 nm) of the spectrum, although contrary to the literature (Clark, 1999; Stenberg and Viscarra Rossel, 2010), the visible part is not so typical for characterising most soil properties. It is an important result because using the visible part of the spectrum, many successful predictions can be made for important soil properties, such as clay content, TOC and TN. A visible reflectance spectrometer (350-700) is less complicated and cheaper than those of vis-NIR and mid-infrared (MIR) spectrometers. Data handling and analysis is also easier with a relatively low number of wavelengths.

5.4.3. Biplot of RDA loadings of the first two ordinates

Principal components analysis (PCA) and redundancy analysis (RDA) are the ordination analyses in which biplots are used to display the relationship between ordination scores and loadings associated with any two principal components (PCs) or principal axes. In PCA analysis when only spectral wavelengths were used, the first two PCs explained about 99 % variation in the wavelengths in each field. Then RDA analysis was used to see correlations among different soil properties and between soil properties and different wavelengths. The RDA loadings of the first two principal axes of Field 3 were plotted (Figure 5.2) using Canoco software (ter Braak, 1988). Correlations between the predictor variables (i.e. wavelength numbers) and the response variables (i.e. soil properties) are visualised from the length of arrows and the angle between them. Angles between any two variables indicate the sign of correlation, which is positive when the angle is sharp and negative when the angle is larger than 90 degrees. The distance of a variable from the origin is a measure of fit for a variable (ter Braak, 1988). Soil properties showed good correlations among themselves. For example, EC, TOC and CN had good correlations with one another. The $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$ were also highly correlated because they are clustered together. Sand was negatively correlated, whereas silt was positively correlated with $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$. Nearly all predictor variables (wavelengths) were clustered together at the right of PC1 (Figure 5.2, left). This implies that the predictor variables are highly correlated with one another and the first axis explains the most variation in predictor variables. In Figure 5.2 (left) all predictor variables are shown, whereas Figure 5.2 (right) shows only selected predictor variables of Field 3 as listed in Table 5.2. Clay content showed a good positive correlation with wavelength 354 and TOC indicated a good positive correlation with wavelengths 350 and 351 and negative correlation with other wavelengths clustered on the right. Similarly, TN was positively correlated with wavelength 371 and negatively correlated with many wavelengths including 369. Silt was also correlated with the cluster of wavelengths. Correlations between soil properties and different wavelengths shown in the biplot are consistent with those listed in Table 5.2 used for SMLR, although highly collinear predictor variables are automatically removed by the SMLR method. This implies that selection of fewer wavelengths using PCA or SMLR analysis is possible and selected variables by both methods can provide correlations with soil properties comparable with that of PLSR.

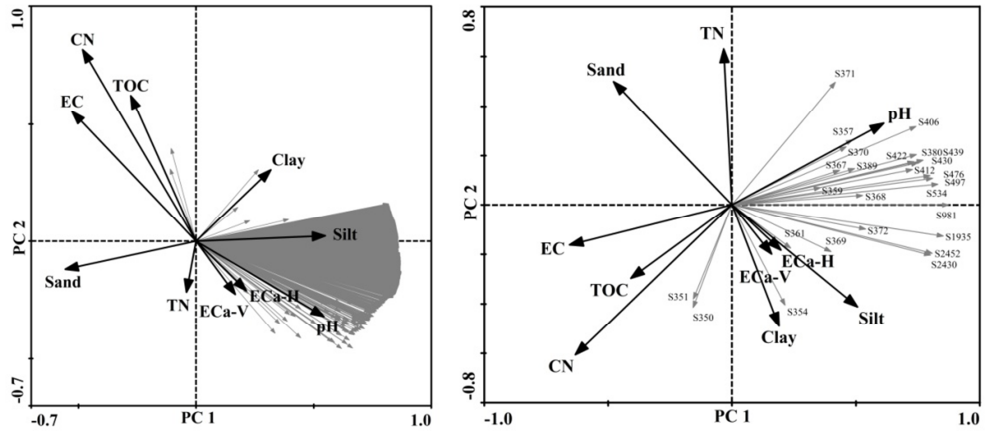

Figure 5.2. *PCA loading plot showing all wavelengths (left) and selected wavelengths (right) indicating correlation with soil properties. Bold arrows belong to soil properties and dim arrows belong to spectral wavelengths. Note that in the plot on the left, the labels of most dim arrows were overlapping (the swarm in the right bottom corner) and therefore were removed to improve readability.*

5.4.4. Predictability of individual sensors

Both vis-NIR spectrometer and EM38 showed different levels of accuracy to predict soil properties. The reason is that each sensor responds differently to different soil properties based on its fundamental principle. Results of individual as well as data fusion methods are shown in Table 5.3. In individual methods, the vis-NIR spectrometer produced better predictions for all soil properties in three fields than did the EM38. It was not surprising that EC_a did not correlate so well with the point measurements of soil properties because the sensed soil volume using the EM38 was about 1 m^3, whereas soil measurements were restricted to the top 0.30 m soil depth. This implies that the EM38 is not actually designed for predicting soil properties in a small part of its volume of influence. Better results may be obtained when the entire corresponding soil volume is considered for soil sampling to incorporate the effective sensitivity of the EM38. The weak correlation between EC_a and soil properties of the top 0.30 m depth indicates that the soils of the three fields are not vertically homogeneous. Furthermore, integrated response of multiple soil properties contributing to EC_a was also another factor for reduced correlation between EC_a and soil properties as the EM38 measures overall soil variability. In contrast, the vis-NIR spectrometer captures soil information regarding soil constituents better than the EM38 because soil physical and chemical properties have specific absorption dips on vis-NIR spectra.

For the spectral data of vis-NIR spectrometer, clay, silt and sand showed a higher accuracy of prediction ($R^2 \geq 0.70$; RPD ≥ 1.78) and pH and EC showed a lower accuracy of prediction ($R^2 \leq 0.41$; RPD = 1.31) in Field 1. Low accuracy for pH and EC is logical because these soil properties do not have direct responses in the vis-NIR spectra and their prediction using vis-NIR spectra cannot be guaranteed. It should be noted that in Field 2 the R^2 values for clay, silt and sand for vis-NIR spectrometer were good ($R^2 \geq 0.67$), but the RPD values were very low

(RPD ≤ 1.39), which is very unusual. This is probably due to high RMSEP values for these properties. The highest accuracy in Field 2 was noticed for TOC (R^2 = 0.93; RPD = 2.80). In Field 3, clay content and TN were predicted with lower accuracies (R^2 ≤ 0.45; RPD ≤ 1.32). The highest accuracy was observed for CN (R^2 = 0.79; RPD = 2.19). Although pH and EC do not have direct responses in vis-NIR spectra, they were predicted with a high accuracy in both Field 2 and 3 (R^2 ≥ 0.77; RPD ≥ 1.85).

Table 5.3. *Validation results of predicted soil properties using individual as well as data fusion methods*

Soil property	Individual methods						Sensor data fusion methods								
	Vis-NIR sensor			EM38 sensor			SMLR			PLSR			PCA+SMLR		
	R^2	RMSE	RPD	R^2	RMSE	RPD	R^2	RMSE	RPD	R^2	RMSE	RPD	R^2	RMSE	RPD
Field 1															
Clay (%)	0.79	1.80	2.24	0.28	3.41	1.19	0.88[a]	1.43	2.82	0.87[a]	1.45	2.79	0.82[b]	1.74	2.33
Silt (%)	0.70	1.62	1.78	0.34	2.43	1.19	0.85[a]	1.17	2.46	0.84[a]	1.21	2.38	0.87[a]	1.09	2.64
Sand (%)	0.72	2.94	1.90	0.39	4.45	1.26	0.85[a]	2.16	2.59	0.84[a]	2.22	2.52	0.77[b]	2.63	2.12
EC (mS m^{-1})	0.39	5.02	1.31	0.28	5.50	1.19	0.67[a]	3.72	1.77	0.69[a]	3.61	1.82	0.72[a]	3.49	1.88
pH	0.41	0.14	1.31	0.40	0.15	1.26	0.67[a]	0.11	1.74	0.76[a]	0.09	1.98	0.68[a]	0.11	1.73
TOC (mg g^{-1})	0.65	0.91	1.70	0.09	1.48	1.04	0.65	0.92	1.67	0.71[a]	0.84	1.83	0.67	0.89	1.74
TN (mg g^{-1})	0.64	0.11	1.48	0.14	0.15	1.09	0.58	0.11	1.48	0.67[b]	0.11	1.50	0.69[b]	0.11	1.54
CN	0.70	0.62	1.77	0.09	1.04	1.05	0.67	0.65	1.68	0.75[b]	0.54	2.01	0.74[b]	0.56	1.95
Field 2															
Clay (%)	0.67	0.42	1.28	0.49	0.62	0.86	0.52	0.41	1.30	0.75[a]	0.27	2.02	0.79[a]	0.30	1.78
Silt (%)	0.80	2.63	1.39	0.09	3.28	1.12	0.86[a]	2.20	1.66	0.78	2.28	1.61	0.77	2.82	1.30
Sand (%)	0.72	2.66	1.31	0.05	3.21	1.08	0.75[b]	2.24	1.56	0.71	2.12	1.64	0.75[b]	2.15	1.62
EC (mS m^{-1})	0.77	1.19	1.85	0.01	2.16	1.02	0.81[b]	1.29	1.70	0.70	1.28	1.72	0.81[b]	1.29	1.70
pH	0.90	0.15	2.40	0.20	0.39	0.92	0.89	0.15	2.44	0.90	0.15	2.40	0.90	0.14	2.48
TOC (mg g^{-1})	0.93	0.73	2.80	0.49	1.88	1.08	0.61	1.19	1.70	0.94	0.79	2.56	0.49	1.45	1.40
TN (mg g^{-1})	0.59	0.06	1.47	0.01	0.12	0.75	0.60	0.06	1.53	0.59	0.06	1.46	0.71[a]	0.05	1.82
CN	0.68	1.19	1.65	0.40	1.97	0.99	0.44	1.43	1.37	0.85[a]	0.84	2.34	0.64	1.25	1.57
Field 3															
Clay (%)	0.39	1.39	1.27	0.20	1.62	1.09	0.48[a]	1.28	1.38	0.54[a]	1.19	1.48	0.34	1.47	1.20
Silt (%)	0.72	2.52	1.70	0.71	2.31	1.86	0.76[b]	2.28	1.88	0.78[a]	2.03	2.11	0.79[a]	2.09	2.06
Sand (%)	0.69	3.06	1.67	0.72	2.78	1.84	0.87[a]	1.97	2.59	0.83[a]	2.17	2.35	0.87[a]	2.14	2.39
EC (mS m^{-1})	0.79	3.14	2.04	0.21	5.71	1.12	0.63	4.10	1.56	0.80	3.29	1.94	0.79	3.16	2.02
pH	0.79	0.06	2.16	0.21	0.10	1.12	0.78	0.05	2.14	0.85[a]	0.05	2.54	0.65	0.08	1.45
TOC (mg g^{-1})	0.76	0.56	2.01	0.06	1.08	1.04	0.86[a]	0.41	2.70	0.73	0.60	1.88	0.52	0.82	1.37
TN (mg g^{-1})	0.45	0.10	1.32	0.28	0.11	1.19	0.50[b]	0.10	1.30	0.59[a]	0.09	1.54	0.41	0.11	1.28
CN	0.79	1.75	2.19	0.02	3.73	1.03	0.91[a]	1.25	3.07	0.86[a]	1.45	2.65	0.75	1.96	1.96

The RMSE is the RMSEP (root-mean squared error of prediction).

[a] Predictions are significantly improved at 0.01 probability level.

[b] Prediction are significantly improved at 0.05 probability level.

Correlations between EC_a data and soil properties were generally lower for all soil properties in the three fields except silt and sand content in Field 3, where these soil properties were predicted with the same accuracy as with the vis-NIR spectrometer ($R^2 \geq 0.71$; RPD ≥ 1.84). Prediction accuracy was generally low for all other soil properties ($R^2 < 0.50$; RPD ≤ 1.26). Among low correlations between EC_a and soil properties, clay, silt, sand, EC and pH showed generally better predictions than the other soil properties. The TOC and TN also showed some correlation in Fields 2 and 3. This may be due to their correlation with soil texture, EC and pH.

The reason for low accuracies for EM38 is that soil EC_a (both $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$) is a depth-weighted response of the entire sensed depth (McNeill, 1980). The instrument produces only one EC_a output in each vertical and horizontal dipole mode and does not distinguish the contribution from individual soil properties in EC_a. During data analysis with SMLR, only one of the two EC_a measurements was retained in regression model because both measurements were highly correlated ($R > 0.75$) (Figure 5.2).

5.4.5. Predictability of data fusion methods

Table 5.3 shows that results of individual sensors were improved using fusion approaches for many soil properties.

5.4.5.1. SMLR fusion

The prediction of clay content was improved in Fields 1 and 3, whereas predictions of silt and sand content were improved significantly in all three fields. The prediction of soil EC was also improved significantly in Fields 1 and 3, however, the prediction of pH was only improved in Field 1. Similarly, TOC, TN and CN were only predicted with improved accuracy in Field 3. Overall, clay, silt, sand, EC and pH were predicted with better accuracy. Other soil properties did not show any improvement in prediction accuracy. Better results were found in Field 1 and 3 than in Field 2. Lower prediction accuracies for some soil properties indicate the poor ability of SMLR to deal with the multi-collinearity among the predictor variables. Adding extraneous variables to a model manually tends to reduce the precision, increases error and reduce prediction ability, especially if the extra variables do not produce an increase in R^2 values (Rawlings et al., 1998).

5.4.5.2. PLSR fusion

Predictions of clay and CN were significantly improved in all fields using the PLSR fusion method than those in the individual methods. Although CN did not show any correlation with EC_a data (except in Field 2), the prediction of this property was significantly improved in all fields. Predictions of silt, sand, pH and TN were significantly improved in Fields 1 and 3, however, predictions were not improved in Field 2. Predictions of soil EC and TOC were significantly improved in Field 1 and were slightly diminished in Fields 2 and 3. As in SMLR fusion, best results were found in Fields 1 and 3, where predictions of all soil properties were improved. Field 2 (sandy field) showed no improvement in predictions of most soil properties.

The reason for improved predictions for clay, silt, sand, EC and pH in Fields 1 and 3 is that these soil properties showed correlations with individual sensors and were measurable by both sensors, although EM38 yields relatively lower correlations. Fusing the data from both sensors further enhanced their predictions. These results support our hypothesis that the accuracy of predictions of measureable soil properties by each sensor will be improved. Improved soil property predictions for these soil properties imply that PLSR has an ability to handle the data from multiple sensors and deals with the multi-collinearity among sensor outputs and thus enhances the effectiveness of sensor data fusion.

5.4.5.3. PCA+SMLR fusion

In this fusion method, only the prediction of sand content was significantly improved in the three fields. Predictions of clay, silt, EC and TN were significantly improved in two of the three fields. Predictions of soil pH and CN were significantly improved in Field 1. The accuracy of other soil properties was not either improved or diminished using PCA+SMLR method. Overall improved predictions of all soil properties were found for a clayey field (Field 1) and the highest accuracy was found for EC.

5.4.6. Comparison between data fusion methods

The SMLR was able to predict several soil properties with improved accuracy coupling the outputs of both sensors, but not in all fields. The main drawback of SMLR is that it cannot be used for a larger number of predictor variables than the number of observations. Selection of predictor variables is also a difficult task when hundreds of highly collinear wavelengths relate to a soil property with a similar correlation. The ability of SMLR in dealing with the multi-collinearity among the predictor variables is also very poor as compared with PLSR, which can over- or under-estimate the accuracy of predictions. Another issue related to SMLR was about elimination of $EC_{a\text{-}H}$ and $EC_{a\text{-}V}$ values from the regression models during analysis. This can be explained as either EC_a measurements are highly correlated with the spectral data or they are adding subtle or non-significant contribution to the fusion model. The SMLR retains only a few variables that have a significant effect in the model and throws away other relevant or irrelevant information. Adding more variables in a regression model may increase its accuracy, but it can decrease the prediction ability of the model.

The PLSR showed the highest accuracy to predict many soil properties. Results were improved greatly from those of individual sensors. Addition of new predictor variables to models may add more multi-collinearity among them, but gains a modest improvement in the accuracy of PLSR analysis. In this scenario, PLSR has the ability to deal with multi-collinearity among the predictor variables and is not affected by the phenomenon of adding new predictor variables in a model, because it constructs a strong predictor variable from several weak predictor variables. Finally, PLSR detects the main latent structure present in the predictor variables that maximises the explained variance in the corresponding response variable.

The PCA+SMLR yields comparable results to PLSR in Field 1, but yields reduced accuracies in other fields for some soil properties. Slightly lower accuracies in the PCA+SMLR method than the PLSR method can be attributed to the difference in data analysis procedures of the two

methods. For example, PCA is an unsupervised analysis method because it is performed without a consideration of the target variable. In contrast to PCA, PLSR is a supervised analysis method because it maximises the correlation between the predictor variables and a target response variable. There was also the same issue of elimination of EC_a variables from the model by SMLR. In many cases, the regression models did not use EC_a measurements as predictor variables together with PCA scores during fusion. There is also the inability of the SMLR technique to handle outputs of different sensors. This might be because the EC_a is collinear with the PCA scores of soil spectra or they were adding subtle or non-significant information as compared with the PCA scores.

In summary, the proposed data fusion methods have improved the accuracy of predictions for clay, silt, sand, EC and pH significantly, although not in all fields. It should be noted that the performance of data fusion is largely affected by the type of sensors used for data fusion. Better results for performing data fusion are expected where individual sensors also show good correlation with soil properties. In this study, despite very low correlations between EC_a measurements and soil properties, predictions of the measureable soil properties were significantly improved. This is consistent with results from Schirrmann et al. (2011), who reported that the accuracy of measureable soil property (e.g. pH) was improved using a sensor fusion approach having a pH sensor, vis-NIR spectrometer and an EC_a sensor. In our study, besides measurable soil properties, the accuracy of other soil properties that showed lower correlation with EC_a, such as TOC, TN and CN were also improved in some cases. This indicates that the poor correlation of EC_a with soil properties can also enhance accuracy of predictions during fusion. Although results of the three data fusion methods were comparable, PLSR outperformed the SMLR and PCA+SMLR methods. This implies that PLSR has better ability to deal with the multi-collinearity among the predictor variables and handle the data from different sensors effectively. The SMLR method sometimes showed results with low error (RMSE) for some soil properties in calibration models, but those models were unable to generalise when subjected to validation on a separate set of samples and produced large errors. In this case, although SMLR with fewer wavelengths may seem to yield comparable predictions to PLSR, over-fitting is likely. Over-fitted models display very good results in calibration models, but show very low ability to predict soil properties.

From the above results, it is clear that sensor data fusion is advantageous over soil property predictions based on a single sensor. Many possible benefits of fusion can be achieved, such as robust accuracy, extended attribute coverage and complementary information on certain soil properties. Despite a number of potential benefits of sensor data fusion, the approach may be hampered due to the difficulty of handling large volumes of sensory data from multiple sensors/sources, lack of accuracies in positioning systems for using multiple sensors real-time and complex statistical methods to be employed for data fusion.

5.5. Conclusions

Models based on data fusion of an EM38 and a vis-NIR spectrometer predicted clay, silt, sand, EC and pH better than those based on the output of the individual sensors. The accuracy of prediction of other soil properties that show low correlation with the output of one of the sensors, such as TOC and CN, is also improved in some cases. The highest accuracy was found

for clay, silt and sand content. It is expected that the performance of sensor data fusion is largely affected by the type of sensors used for fusion and hence selection of sensors is very crucial.

The three statistical methods tested yielded comparable results and can be used for data fusion. However, PLSR outperformed SMLR and PCA+SMLR to predict some soil properties. The reason is that PLSR has a better ability to deal with the multi-collinearity among the predictor variables and can handle the data from both sensors. The SMLR and PCA+SMLR yielded similar results. The best results were found in a clayey field and the worst in a sandy field. The clayey field showed improved accuracy of predictions for about all soil properties in all fusion methods.

It is concluded that sensor data fusion can enhance the quality of soil sensing in precision agriculture. More efficient statistical data analysis methods are needed to handle a large volume of data effectively from multiple sensors for sensor data fusion.

5.6. Acknowledgements

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Chapter 6

Mapping clay content using geostatistical sensor data fusion

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6.1. Abstract

Precision agriculture needs detailed soil property maps. Proximal soil sensors can improve soil property mapping by providing ancillary sources of information incorporated in geostatistical interpolation. The objective of this study was to map clay content in a small agricultural field near Lelystad, The Netherlands, using geostatistical data fusion of three sensors: EM38, vis-NIR spectrometer and gamma-ray spectrometer. We used and compared four kriging methods: ordinary kriging (OK), universal kriging (UK), co-kriging (CK), and universal co-kriging (UCK). In total we used four covariates from these sensors; one of these was spatially densely measured (^{232}Th), whereas the others were measured at a limited set of soil sampling locations. Cross-validation results indicated that clay prediction was improved using UK, CK, and UCK compared to OK (R^2 value increased from 0.65 to 0.87). Similarly, root-mean squared error (RMSE) was reduced to almost half (from 0.80 % to 0.47 %) for UCK compared with OK. The UCK map also showed overall reduced kriging standard deviation values in the entire field. This study demonstrates that combining information from multiple sensors can improve prediction compared to prediction with information from one sensor. This clearly indicates that data fusion from multiple sensors makes sense.

Keywords: Geostatistical data fusion; universal kriging; co-kriging, universal co-kriging; clay content.

6.2. Introduction

Precision agriculture needs detailed soil information in terms of contour maps of soil properties characterising within-field variability (Goovaerts and Kerry, 2010). The essence of precision agriculture is to manage our base resources in a sustainable manner and to apply farm inputs, such as fertilisers, irrigation and pesticides on a location-specific basis that helps to save costs, improve production and reduce the impact on the environment (Whelan, 2007). The map of a desired soil property can be made using conventional soil sampling followed by laboratory analysis; however, this requires a substantial amount of time and money because dense sampling is required to obtain accurate maps. Budget constraints may therefore cause that a detailed and accurate soil map that can distinguish differences within the field necessary for implementing precision agriculture cannot be based on observations of the target soil property only. Given this, soil sensors can potentially provide a solution by including soil sensor data as covariates in the mapping and hence improving the accuracy of soil property prediction. Ancillary data from these sensors provide a dense cover of the field and are relatively inexpensive to obtain (Goovaerts and Kerry, 2010). Clearly, the accuracy of the resulting map depends on the strength of the relationship between the sensor's output and the laboratory measured soil property and is not guaranteed to substantially improve the mapping.

Geostatistics is a branch of spatial statistics that deals with spatially continuous phenomena, such as soil or hydrological properties. Typically these properties are not known everywhere and are therefore modelled as outcomes of a random process, for which a geostatistical model is defined and calibrated from the available data. Next, the geostatistical model is applied to interpolate between observation locations and create a map of the target variable. Geostatistics has been widely adopted for attribute mapping in various disciplines, such as mining, hydrology, petroleum engineering, meteorology, hydrology, soil science, ecology and precision agriculture (Oliver, 2010). Different soil attributes were mapped using geostatistics since the early 80's (Burgess and Webster, 1980; McBratney and Webster, 1983; Odeh et al., 1995), but in precision agriculture, geostatistics appeared later. Mulla and Hammond (1988) mapped patterns of soil nutrients, such as P and K from large irrigation circles. At the same time geostatistics was also used in an agricultural context (Miller et al., 1988; Webster and Oliver, 1989).

Many authors used geostatistics to map single soil or crop attributes with ordinary kriging (Burgess and Webster, 1980; McBratney and Webster, 1983; Lesch et al., 1992; Triantafilis et al., 2001; Hossain et al., ; Martínez et al., 2010). However, using ancillary data from different remote and proximal sensors can improve spatial prediction when ancillary data are correlated with the attribute of interest. For example, in soil property mapping it makes sense to try and incorporate information from soil sensors to improve the accuracy of the interpolated map. Literature reveals that incorporating information from ancillary sources to map soil properties has not yet been widely used in precision agriculture (Goovaerts and Kerry, 2010), although recently some studies were reported (Castrignanò et al., 2012; De Benedetto et al., 2012). Some authors used sensors' data to improve soil property predictions and yield maps (Triantafilis et al., 2001; Kozar et al., 2002; Dobermann and Ping, 2004; Baxter and Oliver, 2005; Tarr et al., 2005; Ge et al., 2007; Lesch and Corwin, 2008). However, in most

studies only one covariate from a sensor's output has been used for mapping soil properties. Using more covariates from multiple soil sensors may further improve the accuracy of soil property prediction and mapping.

The objective of this study was to map clay content in a small agricultural field near Lelystad, The Netherlands, using geostatistical data fusion of ancillary information of three proximal sensors: EM38, gamma-ray spectrometer and vis-NIR spectrometer.

6.3. Materials and methods

6.3.1. Soil sampling and sensor data acquisition

The study field was located at the experimental farm of Wageningen University, near Lelystad, the Netherlands. The total area of the field is about 2 ha and the texture of the field is sandy loam. Soil samples were taken from 72 locations using transects (Figure 6.1). From each sampling location, soil samples were taken from the top 15 cm soil depth in about 1-m radius from each sampling node. About 5-8 soil cores were collected from each sampling location and bulked to represent the sensing area of an EM38 (Geonics, Limited, Ontario, Canada) and a passive gamma-ray spectrometer (Soil Company, Limited, The Netherlands) with thallium-activated caesium iodide (CsI-Tl) detector crystal. From each soil sampling location, the apparent soil electrical conductivity (ECa) using EM38 was measured in both horizontal and vertical dipole modes (McNeill, 1980). The gamma-ray data were acquired real-time from the field. The spectrometer was moved in the field at about 1.2 m s^{-1} mounted on a wheel barrow. We selected eight rows along the length of the field about 10 m apart to collect gamma-ray data. Gamma-ray data were collected at 1 Hz frequency from about 2000 locations together with the associated GPS locations (Figure 6.1). The coordinate system used in this study was the Dutch National Grid System (RD-coordinates; Rijksdriehoekstelsel) (De Bruijne et al., 2005). Soil samples were air dried, passed through a 2-mm sieve and divided into two halves after homogenisation. The first half was analysed for soil texture using the hydrometer method (Soil Survey Staff, 2009). The other half was used to measure soil reflectance in the laboratory using a vis-NIR spectrometer (ASD FieldSpec Pro FR®, Analytical Spectral Devices, Inc., Boulder, Colorado, USA).

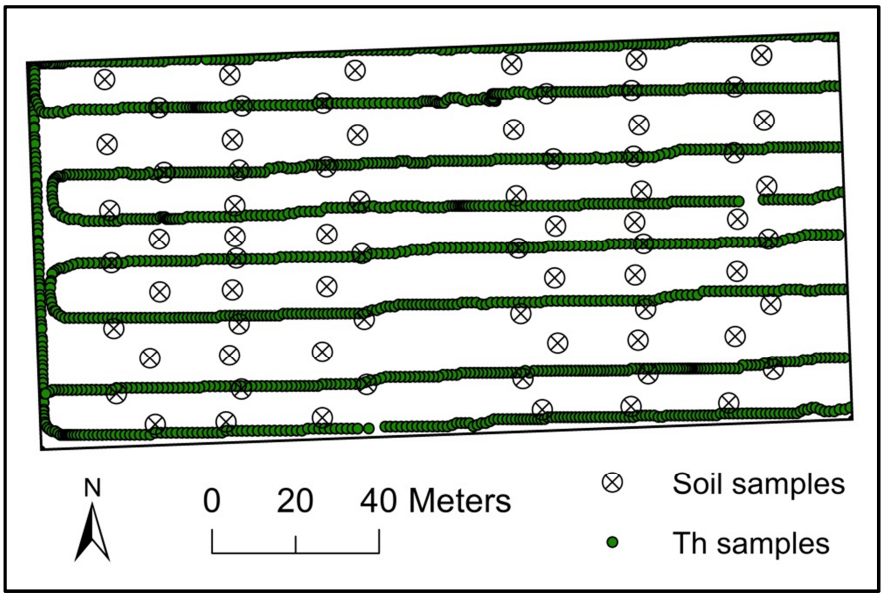

Figure 6.1. *Study area with observation locations. Circles with crosses are the soil sampling locations and other dots are gamma-ray sampling points.*

6.3.2. Selection of covariates for analysis

The outputs of EM38 and vis-NIR spectrometer were measured only at the soil sampling locations, whereas the gamma-ray spectrometer scanned the field real-time at a higher spatial resolution. We omitted the ECav (vertical dipole mode reading of EM38) from the analysis because it was strongly correlated with ECah (horizontal dipole mode reading of EM38) and had a weaker correlation with clay content (see Figure 6.2 in the results and discussion section). Therefore, we only used the ECah for analysis and statistical inference. The vis-NIR spectrometer measured soil spectra containing 2151 wavelengths from 350 nm to 2500 nm. To reduce the number of variables to be used as covariates, we performed stepwise multiple linear regression analysis. In the end, two wavelengths (W388 and W1197) showed the highest correlation and were chosen to be used as covariates. Similarly, gamma-ray spectrometer measured gamma radiation in 256 energy channels (bands). Gamma-ray data were converted to elemental concentrations of three radionuclides, i.e. ^{40}K, ^{238}U and ^{232}Th and total counts (TC) using the full-spectrum analysis method (Hendriks et al., 2001). The scatter plots between clay content and the selected covariates are shown in Figure 6.2. The highest correlation was found between clay content and ECah (R^2 = 0.64). As gamma-ray measurements were not measured directly on the sampling nodes, first we interpolated these values using Inverse Distance Weighting (IDW) and plotted the interpolated ^{40}K, ^{232}Th, ^{238}U and TC values at the sampling nodes against clay content. Clay content showed a strong correlation with ^{232}Th and poor correlation with the other radionuclides (Figure 6.2). Hence, only ^{232}Th was used as a covariate for analysis. In total, we had one target variable (clay

content) and four covariates (ECah, ^{232}Th, W388 and W1197) to be used in the geostatistical analysis.

6.3.3. Kriging methods

The most common geostatistical interpolation method is ordinary kriging (OK). OK uses information only from the target variable (clay content) and starts by estimating a semivariogram from its observations. However, to include also ancillary data from the three sensors, more advanced kriging methods must be used. One of the covariates (concentration of thorium, ^{232}Th) was measured with a denser spatial resolution than others. For this covariate, we used universal kriging (UK). Other covariates, e.g. ECah and vis-NIR soil reflectance, were measured only at the soil sampling locations. To incorporate information from these covariates, we used co-kriging (CK). For further improvement in clay prediction, we used universal co-kriging (UCK) to incorporate information from all three sensors in one model. Finally, we compared the accuracies of clay prediction of these multivariate geostatistical methods with those obtained for OK.

6.3.4. Geostatistics

Classical statistical methods, such as regression, make the basic assumption that all observations are independent and hence ignore spatial correlation (Webster and Oliver, 2007). Reality, however, typically shows that observations that are spatially nearby are more similar than observations far apart. Geostatistics offers a way to describe the spatial continuity of natural phenomena and provides adaptations of classical regression techniques to take advantage of the spatial correlation (Isaaks and Srivastava, 1989). The structure in the spatial distribution of environmental variables therefore calls for the application of geostatistics. The main goal of geostatistics is to build a model of a spatial random variable based on observed data and covariates and use this model to predict its value at an unobserved or unvisited location from the covariates at the target location and from observations at nearby locations. A detailed description of the mathematics behind geostatistics is beyond the scope of this paper. We give a brief summary and refer interested readers to the corresponding original works.

Consider a target variable $z(\mathbf{x})$, in our case the clay content of the topsoil that can vary continuously in geographic space (as indicated by the spatial coordinate, $\mathbf{x}$). In geostatistics, $z(\mathbf{x})$ is interpreted as a realisation of a random function $Z(\mathbf{x})$, for which a statistical model is defined. The property takes values $z(\mathbf{x}_i)$ at observation locations $\mathbf{x}_i$, where $i = 1, 2, 3, \ldots N$. If we consider Z at two places, $\mathbf{x}$ and $\mathbf{x}+\mathbf{h}$, where $\mathbf{h}$ is a distance vector, known as the lag, then the so-called semivariance is defined as (McBratney and Webster, 1986):

$$\gamma(\mathbf{h}) = \frac{1}{2} E[\{Z(\mathbf{x}) - Z(\mathbf{x}+\mathbf{h})\}^2] \qquad \textit{Equation 6.1}$$

here, E[·] means mathematical expectation. Note that Equation 6.1 implicitly assumes that the semivariance only depends on the separation vector **h,** and not on the locations **x** and

x+**h**. This assumption is the part of the second-order stationarity assumption, which states that (Webster and Oliver, 2007):

1. The mean of *Z* is constant and hence does not depend on **x**, i.e. E[*Z*(**x**)] = μ. In practice, this assumption only makes sense if there is no obvious spatial trend.
2. The variance of *Z* is finite and constant, i.e. var[*Z*(**x**)] =E[{*Z*(**x**) – μ}^{2}] = σ^2.
3. The semivariance of *Z* is independent of **x**, e.g. E[{*Z*(**x**) –*Z*(**x**+**h**}^{2}]= 2γ(**h**)

The semivariogram is defined as the function that relates γ to **h**. Spatial patterns are usually described using the experimental semivariogram $\hat{\gamma}(\mathbf{h})$, which measures the average dissimilarity between data separated by vector **h**. It is computed as half the average squared difference between the components of data pairs as given in Equation 6.2 (McBratney and Webster, 1986; Goovaerts, 1999):

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}[z(\mathbf{x}_i) - z(\mathbf{x}_i + \mathbf{h})]^2 \qquad \textit{Equation 6.2}$$

where, *N*(**h**) is the number of pairs of sites being spaced **h** apart. A further assumption is to assume that the semivariance only depends on the Euclidean distance |**h**| between locations, and does not depend on direction. This so-called isotropy assumption is also made in this work.

6.3.5. Ordinary kriging

Given the geostatistical model and underlying assumptions, kriging is optimal among all linear spatial interpolation procedures, as it is unbiased and yields the minimal prediction error variance (Stein and Corsten, 1991). The simplest form of kriging is ordinary kriging (OK), in which predictions are a weighted average of the observations as in Equation 6.3 (Webster and Oliver, 2007):

$$\hat{z}(\mathbf{x}_0) = \sum_{i=1}^{N}\lambda_i \,.\, z(\mathbf{x}_i) \qquad \textit{Equation 6.3}$$

where, $\hat{z}(\mathbf{x}_0)$ is the predicted value of the target variable at an unvisited location $\mathbf{x}_0$ and λ_i are the ordinary kriging weights that depend on the semivariogram of the variable. The kriging prediction variance is obtained as in Equation 6.4:

$$\sigma^2(\mathbf{x}_0) = \sum_{i=1}^{N}\lambda_i \,.\, \gamma(\mathbf{x}_i, \mathbf{x}_0) + \psi(\mathbf{x}_0) \qquad \textit{Equation 6.4}$$

where, $\gamma(\mathbf{x}_i, \mathbf{x}_0)$ is the semivariance between the *i*th sampling point and the target point $\mathbf{x}_0$ and $\psi(\mathbf{x}_0)$ is a Lagrange multiplier, which is introduced to achieve minimisation.

6.3.6. Universal kriging

In OK, it is assumed that the mean (μ) is constant (Equation 6.5):

$$Z(\mathbf{x}) = \mu + \varepsilon(\mathbf{x}) \qquad \textit{Equation 6.5}$$

where $\varepsilon(\mathbf{x})$ is a zero-mean stochastic residual. When this is not realistic, an extension can be made that includes a non-constant trend or drift as shown in Equation 6.6 (Webster and Oliver, 2007):

$$z(\mathbf{x}) = m(\mathbf{x}) + \varepsilon(\mathbf{x}) \qquad \textit{Equation 6.6}$$

where, $m(\mathbf{x})$ is the trend, which is a deterministic function that is often assumed to be a linear combination of explanatory variables or covariates (Equation 6.7):

$$z(\mathbf{x}) = \sum_{k=0}^{K} \beta_k f_k(\mathbf{x}) + \varepsilon(\mathbf{x}) \qquad \textit{Equation 6.7}$$

where the β_k (k = 0, 1, 2, ... K) are to be estimated coefficients and the $f_k(\mathbf{x})$ are the covariates (known functions of $\mathbf{x}$). Geostatistical interpolation under this model is known as universal kriging. It may also be interpreted as an extension to linear regression (Hengl et al., 2004; Hengl et al., 2007), because unlike linear regression it allows that the stochastic residual $\varepsilon(\mathbf{x})$ is spatially correlated. The prediction of a target variable with UK can only be improved compared to OK if the covariates have a significant correlation with the target variable.

The UK prediction of Z at $\mathbf{x}_0$ from the observations and covariates is given by Equation 6.8:

$$\hat{z}(\mathbf{x}_0) = \sum_{k=1}^{K} \hat{\beta}_k f_k(\mathbf{x}_0) + \sum_{i=1}^{N} \{\nu_i (z(\mathbf{x}_i) - \sum_{k=1}^{K} \hat{\beta}_k f_k(\mathbf{x}_i))\} \qquad \textit{Equation 6.8}$$

where, the regression coefficients β_k and universal kriging weights ν_i are computed from the observations. Note that the universal kriging weights ν_i will typically be different from the ordinary kriging weights λ_i. The UK prediction variance can also be calculated similar to the way it is done for OK.

6.3.7. Co-kriging

Co-kriging (CK) is a multivariate extension of OK when covariates are available that are correlated with the target variable (Journel and Huijbregts, 1978; Stein and Corsten, 1991; Goovaerts, 1999). However, unlike for universal kriging, the covariates are not measured in a spatially exhaustive way, but are only measured at the same locations as the target variable (co-located samples), at other locations, or a combination of these. CK requires that both the target variable and covariates have a spatial structure that can be modelled with a

semivariogram and have a spatially dependent covariance, which is modelled with a cross-semivariogram (Rossiter, 2005). As with UK, the prediction of the target variable will improve only if the covariates have significant correlations with the target variable (Zhang et al., 1992; Odeh et al., 1995; Martinez-Cob, 1996; Wu and Murray, 2005).

CK requires the direct and cross-semivariograms of the target variable and covariates. For cross-semivariograms, the models must lead to a positive definite CK system (Journel and Huijbregts, 1978). Fitting the so-called linear model of co-regionalisation is a safe solution to achieve this, where the shape and range of all semivariograms and cross-semivariograms are the same, but nuggets and partial sills can be different. A cross-semivariogram between any two continuous variables Z_u and Z_v is a measure of the joint spatial variation and can be estimated as shown in Equation 6.9 (Goovaerts, 1999):

$$\hat{\gamma}_{uv}(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}\{z_u(\mathbf{x}_i) - z_u(\mathbf{x}_i+\mathbf{h})\} \times \{z_v(\mathbf{x}_i) - z_v(\mathbf{x}_i+\mathbf{h})\} \qquad \textit{Equation 6.9}$$

The semivariograms and cross-semivariograms are used in co-kriging. The predictions using CK make use of observations of the original variable and the covariates as shown in Equation 6.10:

$$\hat{z}(\mathbf{x}_0) = \sum_{i=1}^{N}\lambda_{ui}\,.\,z_u(\mathbf{x}_{ui}) + \sum_{j=1}^{M}\lambda_{vj}\,.\,z_v(\mathbf{x}_{vj}) \qquad \textit{Equation 6.10}$$

where, N and M are the number of observations of z_u and z_v respectively, measured at the same or different locations and λ_{ui} and λ_{vj} are the weights associated to each sampling point. The CK prediction variance can be calculated similar to the way it is done for OK.

6.3.8. Universal Co-kriging

Universal Co-kriging (UCK) is a combination of UK and CK. First, UK is used to link the target variable with spatially dense/exhaustive measured covariates. Next, the remainder is linked with other covariates that are not exhaustively known using CK.

6.3.9. Evaluation of prediction quality

We used cross-validation to assess the quality of the predictions by different kriging methods, which is a commonly used method in geostatistics (Kozar et al., 2002; Rossiter, 2005; Goovaerts and Kerry, 2010; Oliver, 2010). In cross-validation, each point is held out in turn and the prediction at that point is made from the remaining points using kriging. We used the *gstat* package in R software (Pebesma and Wesseling, 1998; Pebesma, 2004) for data analysis and geostatistical interpolation. Diagnostic measures are the coefficient of determination (R^2), the mean error or bias (ME), the root-mean squared error (RMSE) and the mean squared deviation ratio (MSDR) of the residuals to the prediction errors. For accurate prediction, the ME should be close to zero and the RMSE should be small. The MSDR should

be close to 1, indicating that an appropriate model has been used (Oliver, 2010). The ME, RMSE and MSDR were determined using Equations 6.11-6.13:

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)] \qquad \textit{Equation 6.11}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2} \qquad \textit{Equation 6.12}$$

$$\mathrm{MSDR} = \frac{1}{N}\sum_{i=1}^{N}\frac{[z(x_i) - \hat{z}(x_i)]^2}{\sigma^2(\mathbf{x}_i)} \qquad \textit{Equation 6.13}$$

where $z(x_i)$ is the observation, $\hat{z}(x_i)$ is the prediction, and $\sigma^2(x_i)$ is the kriging variance at x_i, as before.

6.4. Results and discussion

6.4.1. Summary statistics

The scatterplots of clay content and all covariates are shown in Figure 6.2 and Table 6.1 lists summary statistics of clay content and selected covariates (ECah, W388, W1197 and ^{232}Th). The ranges in values of ^{232}Th and ECah were slightly larger than that of W388, W1197 and clay content (Table 6.1). All variables indicated fairly symmetric distributions (-1 <skewness< 1). Transformation when skewness levels are within the usual bounds is not necessary and it is always better to work with the raw data if possible (Oliver, 2010). Only W1197 was the most negatively skewed (-0.70) covariate. Histograms of clay content and selected covariates are shown in Figure 6.3. The histograms gave a weak indication that there were some outliers in the variables. For instance, the histograms of W388 and W1197 indicated that there was one observation in each variable that was very low and isolated from the other observations; however, there was no indication that these were true outliers. From the physical point of view such values are not uncommon. Therefore, these observations were not removed from the dataset.

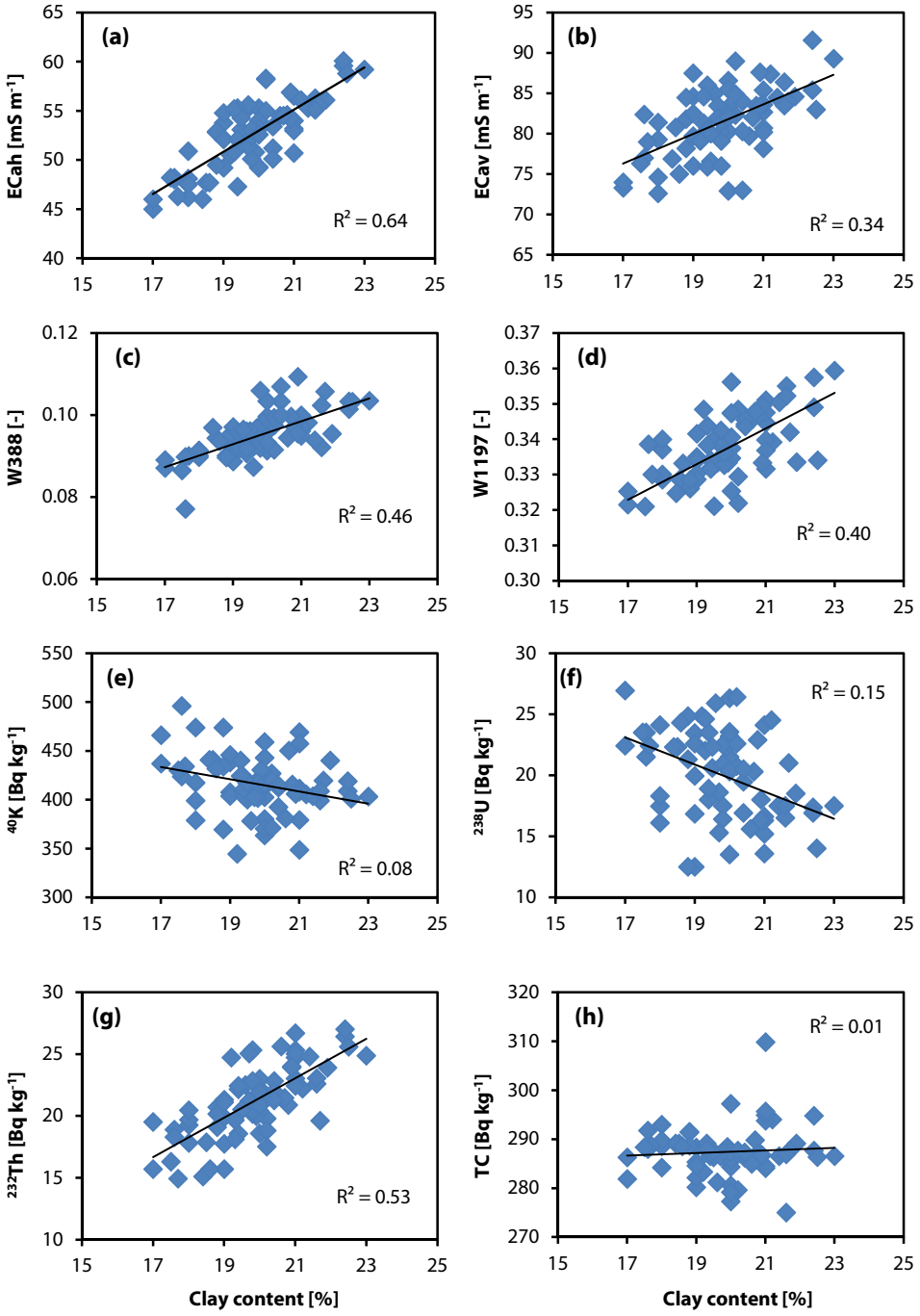

Figure 6.2. *Correlation of clay content with covariates (a) ECah (horizontal mode readings of EM38), (b) ECav (vertical mode readings of EM38), (c) W388, (d) W1197, (e) ^{40}K, (f) ^{238}U, (g) ^{232}Th, and (h) total counts (TC).*

Table 6.1. *Summary statistics*

Soil properties	Sample size	Minimum	Maximum	Mean	Median	SD	Skewness
Clay (%)	72	17.0	23.0	19.8	19.85	1.33	0.02
^{232}Th (Bq kg^{-1})	20099	11.1	26.9	21.1	21.30	1.94	-0.23
ECah (mS m^{-1})	72	45.0	60.1	52.6	53.1	3.6	-0.14
W388 (-)	72	0.08	0.11	0.10	0.10	0.005	0.06
W1197 (-)	72	0.29	0.36	0.34	0.34	0.011	-0.70

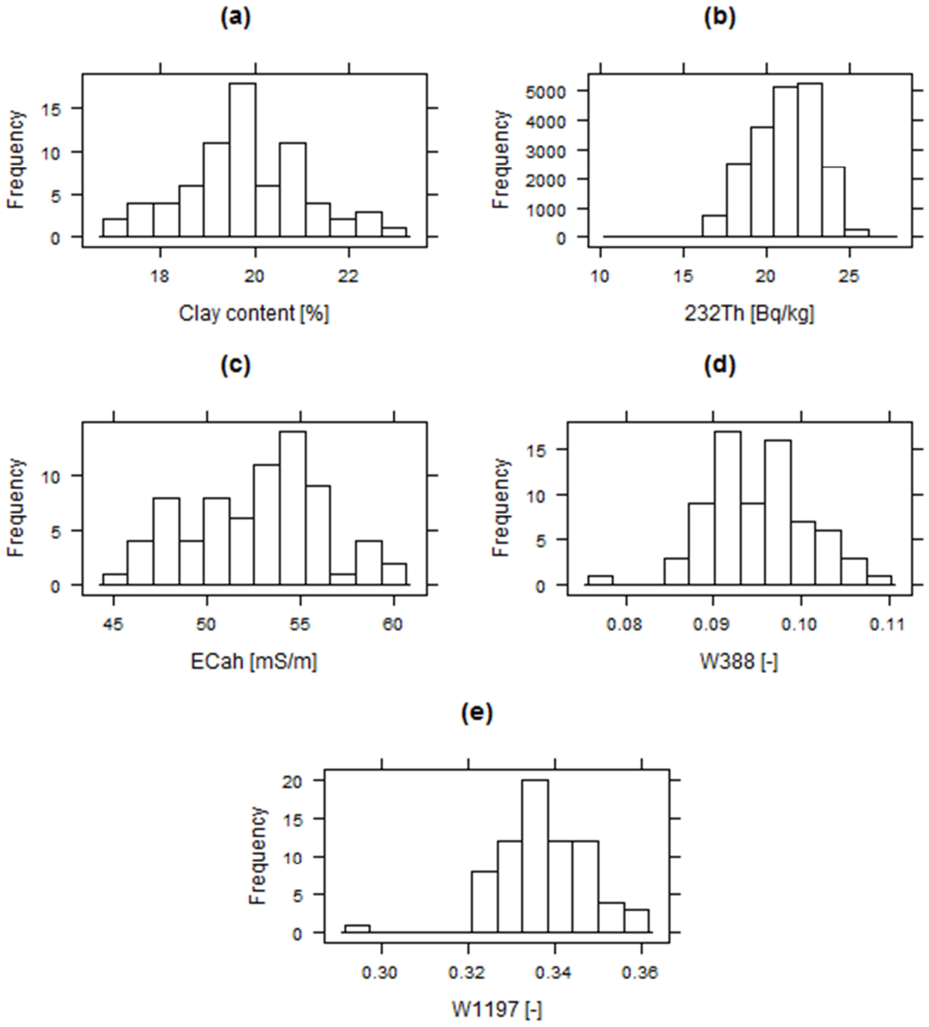

Figure 6.3. *Histograms of (a) clay content, (b) ^{232}Th, (c) ECah, (d) W388, and (e) W1197.*

6.4.2. Semivariograms

Semivariograms of all variables were computed and were fitted to spherical models (Figure 6.4). The semivariogram of clay content indicated a clear spatial structure and was successfully modelled. All semivariograms had a range between 15 and 40 m (Table 6.2). The W388 showed the smallest range meaning that it varies over very short distances and has little spatial structure. However, all variables showed less than 50 per cent nugget to sill ratio which indicates that these covariates can explain spatial variation in the clay content, provided the strength of cross-correlation between clay and covariates is sufficiently large.

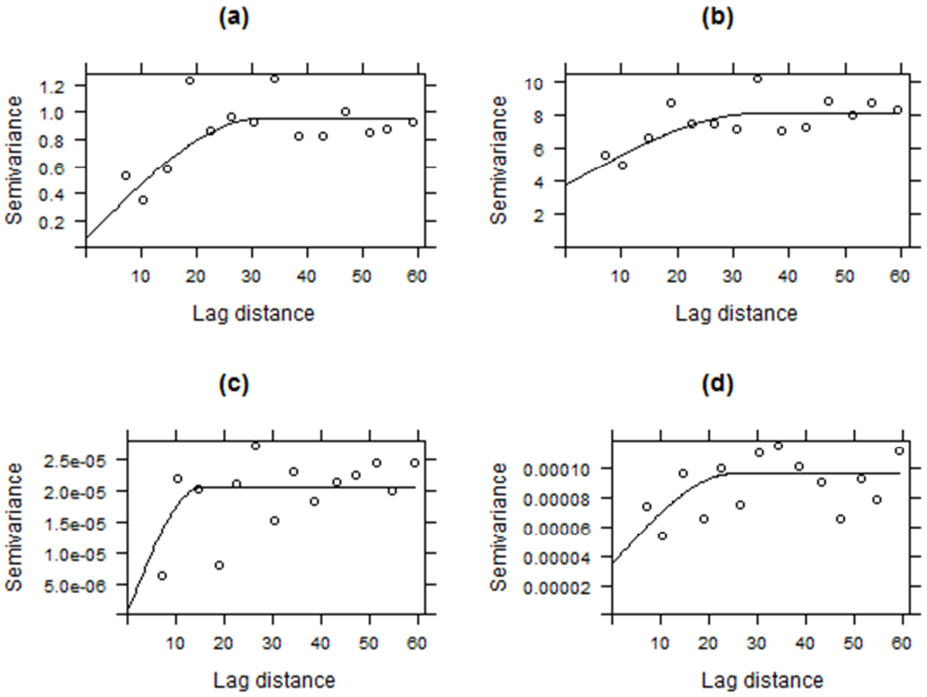

Figure 6.4. *Experimental and fitted semivariograms of variables, (a) clay content, (b) ECah, (c) W388, and (d) W1197.*

Table 6.2. *Parameters of models fitted to semivariograms (direct) of all variables*

Variable	Model	Nugget	Sill	Range (*m*)
Clay	Spherical	0.06	0.96	32.26
ECah	Spherical	3.73	8.14	34.58
W388	Spherical	0	0.00002	15.48
W1197	Spherical	0.000034	0.000096	25.24

For UK, the regression coefficients are shown in Equation 6.14. For CK, we fitted a linear model of co-regionalisation to all direct and cross-semivariograms (Figure 6.5). All models have the same shape and range but different nugget and sill values.

$$Clay = 0.46 \times 232Th + 10.1 + Residual \qquad \textit{Equation 6.14}$$

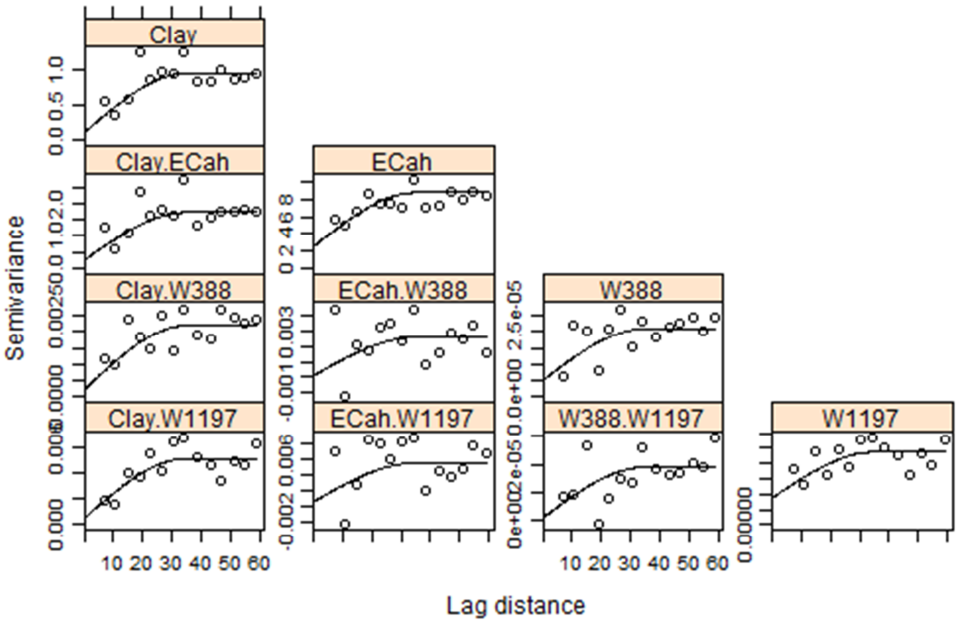

Figure 6.5. *Experimental and fitted direct and cross-semivariograms of variables used in co-kriging (CK).*

6.4.3. Similarities between clay and ^{232}Th maps

The kriged map of clay content and the interpolated map of ^{232}Th with 1 x 1m grid are shown in Figure 6.6. The clay map indicated larger values in the eastern part and smaller values in the western part of the field. It also indicated a few distinct similarities in the spatial patterns with the map of ^{232}Th, especially the contrast between the east and west of the field. However, the spatial patches of ^{232}Th were smaller than the clay content, which suggests that more intensive soil sampling may result in the identification of smaller patches of high and low clay percentages within the field. Despite more detail in the ^{232}Th map, fewer similarities were shown with the clay map. This can be attributed to a low correlation of clay content with ^{232}Th (R^2 = 0.53; Figure 6.2).

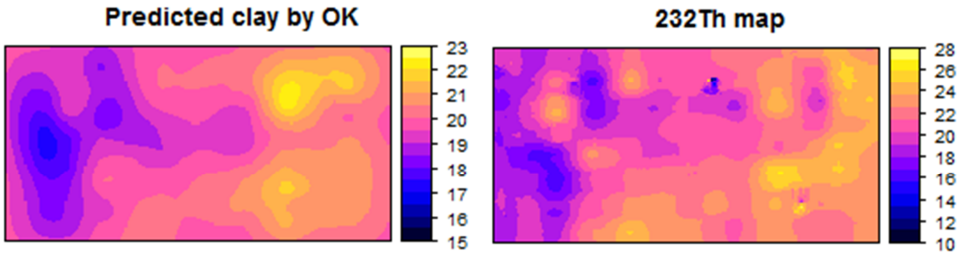

Figure 6.6. *Predicted clay map made by ordinary kriging (OK) and interpolated map of ^{232}Th at 1 x 1 m grid.*

6.4.4. Comparison of predicted clay and kriging standard deviation maps

Predicted clay maps and kriging standard deviation (SD) maps made by the kriging methods discussed above are shown in Figure 6.7. The OK map of clay content was very smooth and showed the main features of the spatial patterns of clay content. The kriging SD map showed the expected low values near the sampling locations and higher values at greater distances from the sampling locations (Figure 6.7).

The UK map of clay content showed more detail because ^{232}Th was measured spatially densely (Figure 6.7). When clay content is predicted using the ^{232}Th covariate, it is possible to identify small-scale variations in the clay content within the field. Despite some obvious similarities, some differences were also found between predicted clay maps made by OK and UK. For instance, slightly higher values in the right side of the UK map make it different from the OK map. Comparing the kriging SD map of UK with that of OK, slightly lower values were found in UK map, although the distribution of the kriging SD was similar for UK and OK. Slightly higher SD values were noticed on soil sampling locations in the UK kriging SD map than the OK kriging SD map.

The CK map (using ECah, W388 and W1197 covariates) of clay content looked very similar to the OK map (Figure 6.7). This means that using the linear model of co-regionalisation and measuring target and auxiliary variables at the same locations, both OK and CK provide approximately the same solution and give similar clay prediction maps. The kriging SD map of CK had slightly smaller values than the OK kriging SD map. This indicates that the model used in CK is not autokrigeable (Wackernagel, 1994). The central part of the map showed lower SD values compared with the OK map.

Combining all covariates in UCK, a more accurate clay map was obtained with more spatial detail (Figure 6.7). This means that combining information from all covariates, clay prediction map can be improved.

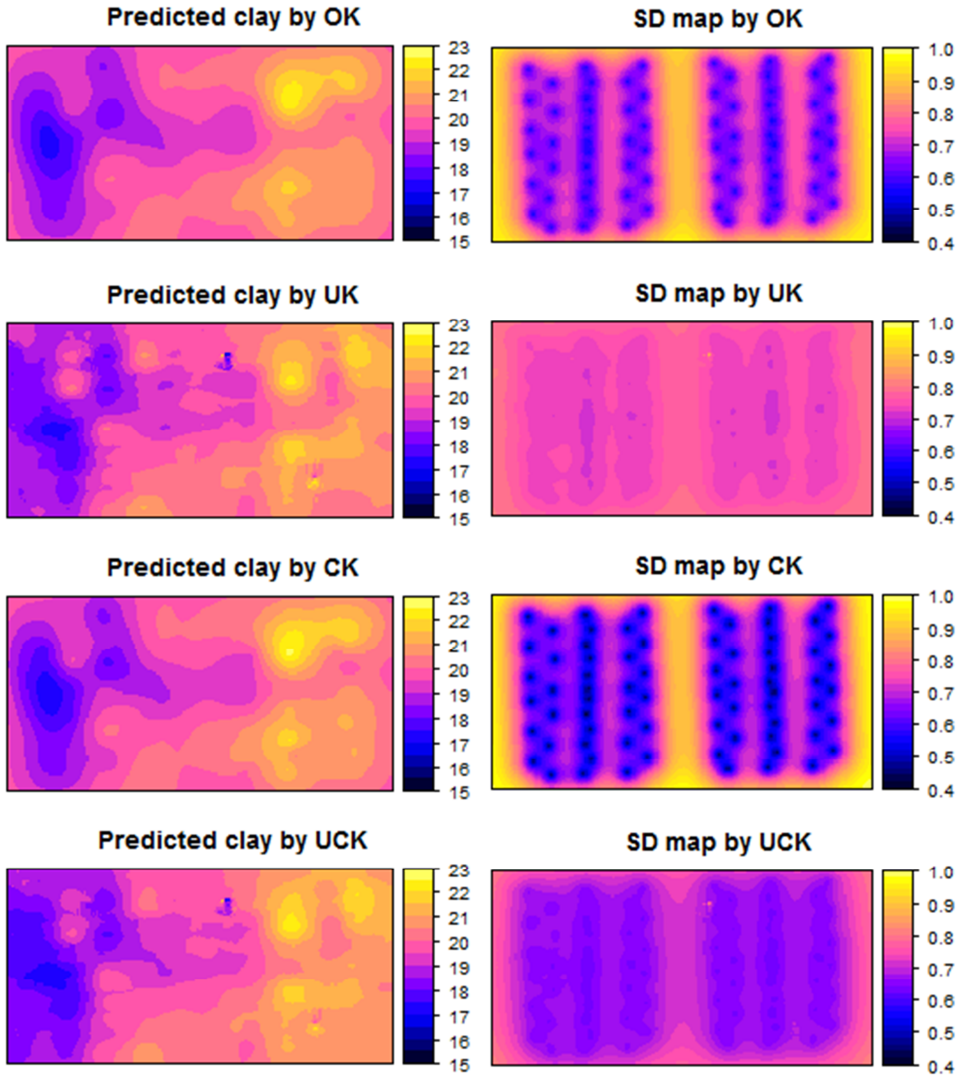

Figure 6.7. *Predicted clay and kriging standard deviation maps made by ordinary kriging (OK), universal kriging (UK), co-kriging (CK), and universal co-kriging (UCK).*

Differences of kriging SD maps were compared between the three kriging methods (Figure 6.8). The difference map of UK and OK kriging SD indicated that there were higher values at the sampling locations and smaller values beyond the sampling location (Figure 6.8). The difference map of CK and OK kriging SD indicated much smaller values (negative) at the sampling locations (Figure 6.8) meaning that CK improves predictions on sampling locations. This is because the CK predictions are based not only on the target variable but also on the covariates measured at the sampling locations. Nevertheless, the SD difference was approximately zero beyond the sampling locations meaning that both OK and CK maps are similar beyond the sampling locations and there is no improvement. The difference map of

UCK and OK kriging SD indicated much smaller values (negative) on most parts of the map. This is based on the extra points of ^{232}Th covariate measured relatively densely. The values in the legends indicated the highest difference (-0.20) between UCK and OK error map. At the sampling locations, the difference of SD values was approximately zero, meaning that there is no improvement.

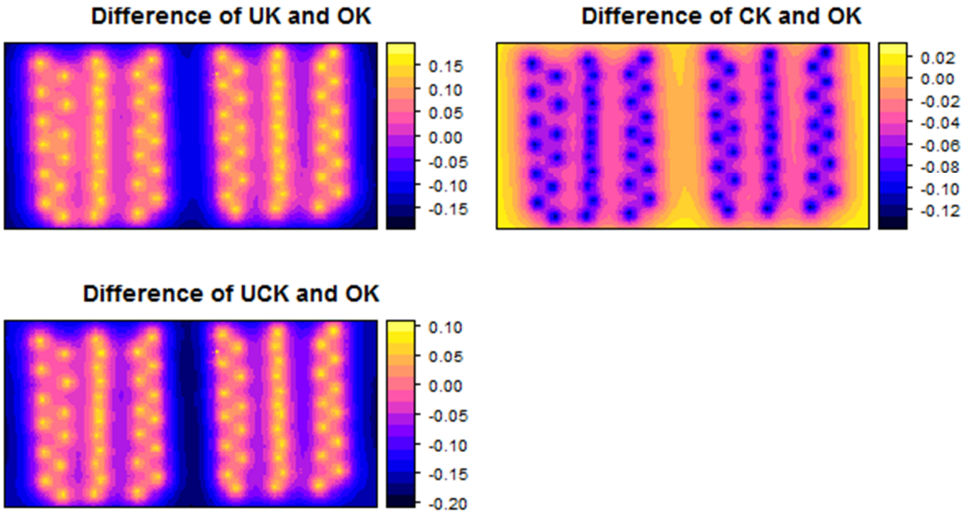

Figure 6.8. *Difference maps of standard deviations made by UK, CK, and UCK with that of OK.*

6.4.5. Cross-validation of kriging methods

Leave-one-out cross-validation results of all kriging methods are shown in Table 6.3. For OK, the ME (bias) is close to zero (-0.0024 %) and RMSE (precision) is 0.80 %. The MSDR value is 1.12, which is close to 1.

Table 6.3. *Leave-one-out cross-validation statistics with all kriging methods*

Method	Covariate(s)	R^2	ME (bias)	RMSE	MSDR
OK	-	0.65	-0.0024	0.80	1.12
UK	^{232}Th	0.70	-0.0025	0.72	0.92
CK	ECah, W388, W1197	0.83	0.0019	0.54	1.22
UCK	^{232}Th, ECah	0.83	-0.0065	0.55	0.86
UCK	^{232}Th, ECah, W388	0.86	-0.0010	0.49	0.94
UCK	^{232}Th, ECah, W388, W1197	0.87	-0.0005	0.47	0.91

For UK, the R^2 value increased from 0.65 to 0.70 and RMSE decreased from 0.80 % to 0.72 %. The error statistics were smaller than for OK, although the differences were small. The value

of MSDR was 0.92, meaning here that the actual residuals are now a bit smaller than the UK predictions, but also in this case it is sufficiently close to 1. Clay prediction was improved, although this was not dramatic. This could be attributed to the weak correlation between clay content and ^{232}Th. The semivariogram of UK residuals indicates that there is little spatial autocorrelation because it has a large nugget (0.4) (Figure 6.9). Despite a good feature-space correlation between clay and ^{232}Th (R^2 = 0.53), predicted clay and kriging SD maps were not improved as expected.

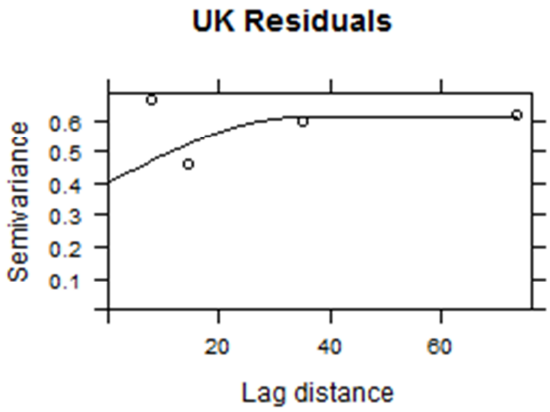

Figure 6.9. *Semivariogram of universal kriging (UK) residuals.*

For CK, where three covariates (i.e. ECah, W388 and W1197) were used together, clay prediction was improved. The R^2 value was increased to 0.83.The RMSE was reduced to 0.54 %, but the MSDR was relatively higher (1.22). This means that the actual residuals are a bit greater than anticipated by the CK model. Although the cross-validation results were improved in CK, these were not as much improved as expected.

For UCK, variables were added step by step in the UCK models and clay spatial prediction was improved gradually as can be seen in Table 6.3. The largest effect was due to the ECah covariate as RMSE was reduced to 0.54 %. The addition of other covariates, W388 and W1197, further reduced the RMSE to 0.47 % and R^2 was increased to 0.87. Table 6.3 showed the obvious improvement in clay prediction from OK to UCK. The final model of UCK showed MSDR value as 0.91.

Validation results showed that comparing OK with UCK, the R^2 value was increased from 0.65 to 0.87 and RMSE was reduced from 0.80 % to 0.47 %, which shows that the precision is improved substantially and clay prediction is improved significantly. Comparing the absolute values of ME and RMSE, the value of ME is much smaller than RMSE, which shows that the bias is not significant in any of the methods and there is no or negligible bias. The difficulty in CK is that the semivariograms and cross-semivariograms must accurately describe the spatial structures. Both target and covariates must have a spatial structure that can be modelled and in addition a spatially dependent covariance must be modelled (Rossiter, 2005). Secondly,

the covariates must have a feature space correlation with the target variable, although this requirement was partly fulfilled because of sufficiently large correlation between clay and all covariates (Figure 6.2). This can also be attributed to the fact that covariates were only measured at the clay sampling locations. To get better benefits of CK we should simulate the situation where the target variable is under-sampled compared with the covariates, but then accommodating different sets of covariates is also a problem. Although CK does not require the ancillary data to be measured at all locations such as UK, its application is more demanding in terms of computing and modelling the semivariograms (Goovaerts and Kerry, 2010).

ECah measured by EM38 showed the highest contribution in data fusion for the improvement of results followed by the ^{232}Th (gamma-ray spectrometer). Covariates from the vis-NIR spectrometer contributed the least in improving clay prediction. This can be attributed to feature space correlation of clay content with these covariates and similar spatial structure of both variables. This can be improved by using information from entire spectrum using multivariate data reduction methods to extract useful information from vis-NIR spectroscopy. Although ^{232}Th was measured real-time densely, its lower correlation with clay content is the main reason of poor prediction using this covariate.

Based on results obtained in this study we expect a better prediction for clay content if ECah was measured with dense spatial measurements. Similarly, this could also be attempted with vis-NIR spectroscopy; however, based on results of this study, we do not expect much improvement of spatially exhaustive measurements of vis-NIR spectroscopy.

6.5. Conclusions

In this study, we attempted geostatistical data fusion of three proximal sensors, EM38, vis-NIR spectrometer and gamma-ray spectrometer, in order to map clay content in an agricultural field. For this, we used and compared four kriging methods: ordinary kriging (OK), universal kriging (UK), co-kriging (CK) and universal co-kriging (UCK). In total, we used four covariates from these sensors; one of these was nearly spatially dense measured (^{232}Th), whereas the others were measured at the soil sampling locations.

Cross-validation results indicate that clay prediction is stepwise improved using UK, CK and UCK. Prediction errors (ME and RMSE) in cross-validation are also reduced to almost half in UCK compared with OK. The kriging standard deviation map of UCK also shows overall reduced values in the entire field. This means that geostatistical data fusion can improve the quality of clay prediction and allows for further reduction of the kriging standard deviation. Fusion of information from sensors is also important when there are few soil samples because this will improve the prediction and identification of small-scale variations in the field. It will allow a better fine-tuning of measures to be taken within a precision agriculture production system. This study has demonstrated that combining information from multiple covariates can improve prediction beyond the case in which information from just one covariate is used. We conclude that data fusion from multiple sensors makes sense.

6.6. Acknowledgements

We acknowledge Higher Education Commission (HEC), Pakistan, for supporting this research by providing a PhD scholarship under the Overseas Scholarship Programme, Phase-II, Batch-I.

Chapter 7

General discussion, conclusions and outlook

7.1. General discussion

7.1.1. Introduction

The topic of the thesis was to evaluate different proximal soil sensors to estimate multiple soil properties and to investigate the potential of data fusion. Two main objectives were formulated. The first objective dealt with the evaluation of proximal soil sensors used in the laboratory, in-situ and on-line (real-time); whereas in the second objective, we performed sensor data fusion of three proximal soil sensors (for example, EM38, vis-NIR spectrometer and gamma-ray spectrometer) and discussed its effectiveness in precision agriculture. In the following paragraphs, the answers to the research questions posed in Chapter 1 will be discussed in a broader scientific/societal context.

7.1.2. Proximal soil sensors for precision agriculture

Commonly used sensors to be used in the laboratory, in-situ in the field and on-line (real-time) were reviewed in Chapter 2, concentrating on proximal sensors suited for monitoring and mapping soils and soil properties. The review shows that many proximal soil sensors will allow rapid and inexpensive collection of soil data. Proximal soil sensors are advantageous over remote sensors because they are more directly related to soil materials and less prone to the effects of vegetation or field cover. However, it was also shown that selecting a suitable and reliable soil sensor for different environmental conditions is difficult.

Manual sampling and laboratory analysis methods are unable to decipher soil variability at the desired level, but it may be possible by taking high density soil measurements using various types of proximal soil sensing principles. With a generally large variation in soil properties, a large number of cheap and less precise measurements are more effective than a few precise and expensive ones. The EM38, vis-NIR spectrometer, gamma-ray spectrometer, ground penetrating radar (GPR) and strength sensors are able to collect soil data every second. Thus, even though these measurements react to the change in more than one soil property, this high resolution information will be adequate as a basis of decision support in precision agriculture.

An important factor to be considered is the volume over which the soil property is measured. Some sensors can measure a very small volume of soil, e.g. vis-NIR, MIR, ISEs, ISFETs, TDR and FDR probes; others need a larger volume of soil, e.g. EM38, ER and GPR. This makes it difficult to combine or compare results from different sensors.

Up to now, these sensors have to be calibrated, commonly for individual fields or soil types. This requires soil samples to be taken followed by a laboratory analysis, which is a time consuming practice. For calibration, simple to complex statistical methods are used and so far no theoretical or generic calibration of these sensing methods has been developed.

Although the sensing principles are not assessed in detail for better understanding of each sensor with the support of basic theory, sufficient information is gathered to understand why various factors will substantially affect the output of the sensing methods. However, the detailed description of basic principles is the limitation of this study.

In a reasonable volume of literature, it has been claimed that precision agriculture is more economical and can have a positive impact on the environment, but its benefits have not been largely studied as main conclusions in both contexts. In economic context, probably the main reason is that precision agriculture is an information technology and estimating the cost of information is difficult and different from other technologies. This involves estimating the cost of obtaining information, analysing this information, making and interpreting the soil property maps, time required to obtain this information and the cost of training a person to operate these technologies. Integrated precision agricultural systems are obviously more profitable than standalone technologies because in integrated systems the cost of equipment, information and humans is spread over multiple operations and the information is organised for multiple purposes and is used for a wider range of activities. Furthermore, the whole farm management will be more economical than a field level management. Similarly in environmental context, the positive impact of precision technologies has not been proved as a main conclusion, but discussed as a residual. The amount of contamination of surface and ground water with pesticides, nutrients, manure, sediments, pathogens and heavy metals needs to be studied. The environmental risks that are responsible for the transport of these materials in soil and water include leaching, de-nitrification, eutrophication, precipitation, runoff, volatilisation and saltation. These environmental risks cannot be changed and will continue in future, but it is possible to modify the loading of fertilisers and nutrients in a field. Here, the challenge is to measure the exact amount of nutrients required by crops/plants and identify the amount of excessive nutrients as environmental risks. The future direction of research is the ability of researchers to pick up these sensitive issues related to environmental impacts that will improve our understanding to protect our environment and increase the efficiency of agricultural production.

Extracting useful information from these sensors has tremendously improved due to advances in mathematical and statistical data analysis methods. Sensors have been becoming faster, more convenient and robust due to advances in electronics. The review shows that proximal sensing methods can facilitate soil inventory mapping, but also that the quality and reliability of soil and environment monitoring with these methods is still very much restricted to specific soil and sensor combinations. Improvement can be sought in the direction of using multi-sensor systems, sensor data fusion, reliable inference systems and focussing on statistical/geostatistical data analysis methods.

7.1.3. Robustness of vis-NIR reflectance spectroscopy models

The vis-NIR spectroscopy is a robust technique for soil sensing and deriving inferences for delineating management zones and site-specific application of inputs. The technique is rapid and cost-effective. Abundant literature is present confirming the potential of this technique for the assessment of soil properties in field-scale studies. However, we tend to expand the effectiveness of this technique to regional, national or global level. In this sense, the development of accurate and robust calibration models for selected soil properties is a crucial prerequisite for successful implementation of this technique for rapid soil analysis. In this perspective, the robustness of vis-NIR reflectance spectroscopy was evaluated by determining soil properties in the field and analysing the data using four different modelling strategies used in literature, such as local models (LMs; models of individual fields), general

models (GMs; models combining different proportions of samples from all fields), spiked models (SMs; models combining all samples from four fields and 10 samples from the target field) and true validation models (TVMs; models combining samples from four fields and predicting in the remaining/target field) (Chapter 3).

For soil properties, such as clay, silt, sand, pH, total organic carbon (TOC) and total nitrogen (TN), LMs yielded the best results among all modelling strategies, which was as expected. General, spiked and true validation models also yielded predictions, but their accuracy was lower than the local models. This implies that large scale applications are difficult to develop because the relationships between vis-NIR spectral data and soil properties are inherently local and depend on the soil type. This is also consistent with the results of Duckworth (1998). Models developed for large geographical areas based on diverse soil samples may provide unacceptable prediction accuracy because of the large variability in soil origin, texture, colour and moisture content. On the other hand, attempts for making global libraries of vis-NIR spectra with associated reference soil property data are important steps to make universal models of vis-NIR spectroscopy although so far results are not consistently positive. These libraries should include samples from all geographical areas.

Furthermore, the model size greatly influenced the accuracy of GMs. The higher the proportion of samples from the target site, the higher the accuracy in the validation set. This requires a large number of samples from all fields to form the calibration set, which thereby reduces the advantage of vis-NIR spectroscopy, since collecting many more samples is then needed. On the other hand, including more samples in a general model from a target field brings more variation in the calibration model and thus enhances its ability to predict similar soil properties. If fields are not much different in soil properties, better and stable predictions are expected with a lower number of samples in the calibration model. True validation models are very difficult to develop until the target fields are similar to the fields used for calibration models. Otherwise, these models fail to predict soil properties (Duckworth, 1998; Viscarra Rossel et al., 2008). However, the SMs gave comparable results with that of the LMs, achieving prediction accuracies that are acceptable for management decisions. The SMs have the potential to predict soil properties with a limited number of samples in the target fields.

We suggest that spiking is effective and should be promoted to predict several soil properties in a field level, although we have to accept a generally lower accuracy than when using LMs. Using spiked and sometimes general models can significantly reduce the number of samples used for analysis and hence will save time and money. Lower accuracy in general and spiked models may be attributed to similar responses of more than one soil property in the vis-NIR spectra that may confuse the generalisation of the method and yield poor results. For instance, clay content and TOC can give similar absorption dips around 2200 nm in vis-NIR reflectance spectrum that ultimately can cause poor predictions of both clay and TOC. In scientific context, the general/global or spiked models of vis-NIR spectroscopy may improve the quality of analytical soil sensing and promote soil sensing methods.

Besides testing different modelling strategies for generalisation of models, there is need to improve the ease of sensor-data collection real-time directly from the field. However, in the field vehicle mounted techniques may be limited to surface sensing and shank-mounted sensors may only be used in flat land up to a few centimetres soil depth. Surface or shallow

measurement of reflectance may not be representative of a wide subsurface soil layer due to vertical variation in soil. Reflectance mapping by reducing the number of wavelengths in a spectrum can also help understand the variation within a field and can be combined with the outputs of other sensors, such as EM38 and gamma-ray spectrometer for better decision making.

7.1.4. Gamma-ray spectroscopy in precision agriculture

Proximal gamma-ray spectroscopy is a relatively new approach for soil sensing and very few studies are reported in literature. Both passive and active gamma-ray spectrometers have been used for soil sensing, however, passive gamma-ray spectrometers gained more importance because they detect natural gamma rays emitted from the soil. Airborne gamma-ray spectroscopy cannot detect small scale variation because of the wide field of view from an airplane. Therefore, proximal gamma-ray spectrometers are gaining more interest in precision agriculture. A proximal gamma-ray spectrometer was evaluated in two fields: a conventional field and an organic field, to predict several soil properties by using full-spectrum analysis (FSA) and the energy-windows (EWs) methods (Chapter 4). Clay, pH, TN and TOC were predicted with a good accuracy using the FSA and the EWs methods. Because clay content was related directly with ^{232}Th, but also with different radionuclides in both depths, this means that clay may also accommodate other radionuclides. Other soil properties do not reveal consistent correlation with any radionuclide and may be measured indirectly due to their correlation with clay content. Predictions were better in the top 0-15 cm soil than the 15-30 cm soil depth. Similarly, good predictions were found in individual fields but when fields were combined results deteriorated. Low prediction accuracies in combined fields are attributed to the fact that a specific radionuclide does not correlate to a specific soil property in different fields during the calibration phase. This result is consistent with those of Van Egmond et al. (2010) and Van der Klooster et al. (2011). As the same value of a soil property can be the result of different (combinations of) parent materials, formation processes, management history, etc. field-level calibration is will be necessary.

Gamma-ray spectroscopy will play a vital role in different aspects of precision agriculture. The advantages of the technique over other proximal soil sensing methods include real-time signal measurement with fewer prerequisites and the measurement is insensitive to vegetation and snow cover up to 5 cm. Proximal gamma-ray spectroscopy can aid in delineating management zones for N, P and K, site-specific application of lime, determining soil compaction and nematode risk and determining heavy metals (e.g. cadmium) in soils. Furthermore, irrigation scheduling can be improved by determining saturated hydraulic conductivity and water holding capacity and yield potential can be determined. In short, gamma-ray data collected at sufficient resolution can reliably depict some of the soil factors related to plant growth in arable farming at the scale suitable for precision agriculture. Further research is recommended to understand the interaction between radionuclides and soil parent materials under different sets of environmental conditions in different types of soil.

7.1.5. Full spectrum analysis versus energy windows method for gamma-ray data analysis

The full spectrum analysis (FSA) method incorporates information from nearly the entire gamma-ray spectrum, whereas the energy windows (EWs) method sums up the intensity of gamma-ray counts from specific portions called windows or regions of interest.

The fact that a small portion of the spectrum is used for analysis in EWs methods implies a risk that a considerable amount of useful information is lost. Therefore, the FSA calibration methods are being advocated. In this study, both methods yielded comparable accuracies in predicting soil properties (Chapter 4). Although the FSA method collects gamma-ray counts from the entire gamma-ray spectrum, radionuclides EWs can also give an accurate indication about the presence of a certain radionuclide and establish similar correlations with soil properties. The radionuclide concentrations in the EWs are therefore the indicator of gamma-ray counts of ^{40}K, ^{238}U and ^{232}Th in the rest of the spectrum.

This study showed that this more simple method for analysing the data gave good results and should be preferred. A simple method is easier to implement and more timely results are obtained for further decision making in soil management.

7.1.6. Data fusion in precision agriculture

A sensing technique that provides information about one soil parameter is considered of limited use when both soil and environmental factors, such as moisture, soil temperature, salts, texture, organic materials and many others influence the output of single sensor systems. This makes the interpretation of corresponding relationship between sensor output and a soil parameter more complex and uncertain. Data fusion is an approach that can improve the performance of a detecting system using various complementary sensors and may produce more effective representation of data. Target information may be obtained with better quality and higher reliability and its inference is potentially more accurate than if it were achieved by a single sensor. Sensor data fusion is an effective approach to enhance the performance of available sensors, which is addressed in Chapter 5.

Three types of fusion methods are common in different applications: redundant fusion, complementary fusion and coordinated fusion. In redundant fusion, each sensor provides the same perception of a target variable. The purpose of this type of fusion is getting better understanding about the target variable from different views. In complementary fusion, each sensor provides disjoint type of information about a target variable. Each sensor has different sensing principle and provides different level of information about a target variable. It is commonly used in soil and environmental sensing. In coordinated fusion, a set of sensors work in a sequence, gather information about a target variable and function accordingly (e.g. in robotics). In view of the above, complementary data fusion was used.

We found better predictions for most soil properties fusing the data from an EM38 and a vis-NIR spectrometer, particularly for clay, silt, sand, EC and pH significantly. This is consistent with results of Schirrmann et al. (2011) and Piiki et al. (2012). As expected, the prediction accuracy was greatly improved in situations where both sensors showed a good correlation

with a certain soil property individually. Therefore, the performance of data fusion is largely affected by the type of sensors used for data fusion. Notwithstanding the many possible benefits of fusion, such as better accuracy and confidence, extended attribute coverage and complementary information on certain soil properties, it was also found that the approach may be hampered by practical requirements. Large volumes of sensory data from the sensors had to be handled, there was a discrepancy in the accuracies in positioning systems for the various sensors, and complex statistical and geostatistical methods had to be employed. So, sensor fusion can only be effective if data from multiple sensors can be efficiently managed.

Other types of fusion, such as redundant fusion may also produce better results in precision agriculture when the target soil is viewed from different angles. Nevertheless, a lower improvement in accuracy is expected than the complementary fusion when there is little difference in sensors' outputs. On the other hand, this type of fusion may be more time-effective because similar signals of redundant sensors will be easier to handle during data analysis. In contrast, signals of complementary sensors need to be brought in accordance for fusion.

While inferences obtained from fusion of sensors can lead to better decision making, such as delineating management zones within a field, harmony among sensors' responses from different parts of the field can also be used as the counter-check of accuracy and reliability obtained by a single sensor.

7.1.7. Statistical methods for data fusion

A large number of methods are being used in sensor data analyses ranging from simple univariate and bivariate methods to more complicated multivariate methods. For data fusion, multivariate methods are needed. In Chapter 5, we applied three commonly used multivariate methods for data fusion: stepwise-multiple linear regression (SMLR), partial least squared regression (PLSR) and principal component analysis combined with stepwise multiple linear regression (PCA+SMLR). All methods yielded comparable results for fusion for some soil properties, with PLSR producing slightly better results. PLSR was found to have a better ability to deal with the multicollinearity among the predictor variables and handle the data from different sensors effectively. This study showed that fusion gives better results, regardless of method used for fusion.

Different statistical methods have different fundamental assumptions, background theory and procedures for analyses. Therefore, different studies with different statistical data analysis methods return different results, which is based on the fact that the nature of the target function has a strong influence of the performance of the different prediction approaches. Unfortunately, so far, there is no universally accepted method that can perform well in all types of conditions to handle all types of data; therefore, more sophisticated methods may be explored. Many other new empirical and data mining techniques have been developed over the past decades for establishing the relationships between sensors' output and soil properties, such as support vector machines (SVM), artificial neural networks (ANN), classification and regression trees (CART), multivariate adaptive regression splines (MARS), boosted trees (BT) and random forests (RF) (Viscarra Rossel and Behrens, 2010). These methods can also be explored for data fusion. If the simpler and more readily available

methods can yield similar results as that of the sophisticated ones then for better science, the simpler methods should be preferred.

7.1.8. Use of geostatistics for data fusion

Multisource data fusion using geostatistics is a key issue in precision agricultural systems, addressing the issue of how to combine data from different (and possibly diverse) sensors in order to make an inference about a target soil property. We mapped clay content using geostatistical data fusion using covariates from three sensors: EM38, vis-NIR spectrometer and gamma-ray spectrometer (Chapter 6). In total, four covariates were used; one of them was spatially exhaustively measured (^{232}Th, gamma-ray output), whereas others were measured at soil sampling locations (ECa and two wavelengths of vis-NIR reflectance). We used univariate geostatistics, ordinary kriging (OK), for mapping just clay content and multivariate geostatistics, such as universal kriging (UK), co-kriging (CK) and universal co-kriging (UCK) for data fusion. Better prediction results were found in UCK when the clay map was combined with the information from all covariates of three sensors. The root-mean squared error (RMSE) of clay prediction was reduced to almost half the original value. The UCK map also showed a reduced error in the entire field, although the error was similar as that in OK at the sampling locations. The RMSE was gradually decreased from OK to UCK. The highest difference was noticed when ECa was used as a covariate in the CK or UCK method. This is because the ECa has very similar spatial structure as that of clay content. Some recent studies also showed the effectiveness of geostatistical sensor data fusion (Castrignanò et al., 2012; De Benedetto et al., 2012).

Geostatistical data fusion can only give improved predictions when covariates show spatial correlation with the target variable. A high correlation between target variable and covariates significantly reduces the number of samples of the target variable (clay) and easy-to-measure sensors outputs can best approximate the spatial structure of the target variable by interpolation. The selection of covariate for dense measurement is also important, which should base on the feature space correlation between covariate and the target variable.

For precision agriculture, a fusion based on geostatistics is more realistic than the classical fusion because soil properties vary in space and time. Using geostatistics, a better management decision can be made for zoning and site-specific application of irrigation and other inputs. Classical statistics focuses on the feature-space correlation between outputs of different sensors and interested soil properties during fusion, whereas geostatistics also integrates location information together with fusion, which helps in interpolating correct soil property maps. Therefore, more focus should be given to develop geostatistical methods for fusion. For geostatistical data analysis, soil property data should also be acquired covering the geographic space and property space for covering all location-induced phenomena in calibration for better decision making in other applications of precision agriculture. Sensor data should follow the proper sampling scheme to be used for different geostatistical fusion methods (i.e. co-kriging, universal kriging, regression kriging), such as spatially exhaustive or less dense measurements.

7.1.9. Relevance of this study in precision agriculture

Precision agriculture is soil and crop management or a "management philosophy" (Schueller), based on technology. In order to come to a management strategy in precision agriculture, a sequence of steps has to be taken, starting with the determination of the variability in the field, an assessment of the cause of this variability, and then to develop a plan of action to deal with this variability according to a certain scenario or goal (e.g. economics, quality or sustainability). Although the end user of precision agriculture will be the farmer, others such as researchers, advisors or extension specialists, machinery manufacturers are important players in this field.

To begin with the farmers: for more than two decades now precision agriculture has been the subject of both fundamental and applied research, instruments to supply data (yields, soil characteristics, etc.) have been made available and some farm equipment is equipped with tools to apply precision agriculture techniques. Yet, only a very small number of farmers in developed countries apply some sort of precision farming. Farmers are faced with challenges that are remote from the underlying technology and therefore may be hesitant to adoption despite the potential benefits. High initial costs of tools and machinery, complexity of the system, uncertain economic returns and lack of awareness are some of the reasons for the slow adoption. Furthermore, the precision agricultural technologies are generally cost-effective for large-scale agriculture, where a narrow profit margin provides an economic advantage to large producers.

A second group of actors consists of those working in extension or advisory either privately, linked to government agencies or commercial institutes or companies producing farm machinery. They more likely will recognise that successful precision agriculture cannot be based on yield monitoring alone; but understand that soil information is crucial as a basis for decisions in precision agriculture. This is particularly so in case of application of machines capable of site-specific action. Even though proximal soil sensors may have brought a number of potential benefits to farmers, this group of actors will realise that exploitation, even of the equipment successfully tested, would still have to prove its value through on-farm experimentation and extension work.

From the above, it is clear that this study, as it addressed the research challenge of how useful information can be obtained from different available proximal soil sensors, will have direct relevance for the research community. This study showed that selection of proper proximal soil sensors for a certain soil property is very important for initiating field measurements, as it will be only after more applied research has been undertaken and clearly has shown which benefits can be expected (both in qualitative and quantitative sense) that commercial parties as mentioned above will step in.

An overview of the most suitable sensors for measuring key soil properties and an evaluation of their accuracy for soil characterisation followed by a discussion on the role of proximal soil sensors in fertiliser recommendation, in modelling crop and soil effects, and in assessing carbon sequestration was given. Visible-near infrared spectroscopy was evaluated to predict

soil properties using different types of modelling strategies to improve the effectiveness of the technique. Similarly, the potential of gamma-ray spectroscopy was evaluated to predict key soil properties. Furthermore, sensor data fusion was performed to improve the accuracy of soil property predictions. Data fusion is the only way to enhance the accuracy of currently available soil sensors. Different statistical and geostatistical methods were used for data fusion and more methods should be explored in this domain. This work will provide the basis to scientists for selection of suitable sensors to be used for a specific application and for data fusion.

A number of questions were raised in the framework of this study but only few of these could be addressed in this thesis. Many other high-level questions remain to be addressed in future-research. For example, what environmental and economical benefits can be gained using proximal soil sensors and data fusion? To what extent can contamination of ground water and soil be reduced by variable rate application of fertilisers? What is the significance if a farmer gets more yields from good spots by applying more inputs and low inputs at poor spots? What is the benefit in terms of yield of within-field management zones and which level of management is needed? The issue of zoning is relevant in the developed countries where large farms need to accommodate larger field equipment and where inherent variation both within and between different fields call for site-specific management.

7.2. Conclusions

Research questions posed in Chapter 1 were addressed in the research chapters and revisited in the general discussion. It is concluded that:

1. Proximal soil sensing technologies are crucial for future farming and many proximal soil sensors allow rapid and inexpensive collection of soil data. However, selecting a suitable and reliable soil sensor for different environmental conditions is difficult. Several factors substantially affect the output of these sensing methods. A large number of cheap, imprecise and high density sensors measurements are more effective than a few "precise" laboratory measured samples, with the understanding that precision in laboratory analysis is not always guaranteed. The fact that different sensors measure a different volume of soil depending on their fundamental principles makes it difficult to combine or compare results. Site-specific calibration of soil sensors is a great hindrance in a widespread utility of proximal soil sensors in precision agriculture. Sensors are becoming faster, more convenient and robust due to advances in electronics. Proximal soil sensing methods nowadays can facilitate soil inventory mapping, but quality and reliability of these methods is still very much restricted to specific soil and sensor combinations.
2. Local models of vis-NIR spectroscopy yield the best results among all modelling strategies. Spiked and general models yield comparable results, but have lower accuracies than the local models. Independent field validation models fail or yield the poorest prediction accuracies. This implies that large scale applications are difficult to develop because the relationships between vis-NIR spectral data and soil properties are inherently local and depend on the soil type. On the other hand,

models developed for large geographical areas based on diverse soil samples may provide unacceptable prediction accuracy because of the large variability in soil origin, texture, colour and moisture content. Future research should be focussed on maximising the accuracy of spiked and global models (global libraries) that will help reduce the cost and time significantly for global soil characterisation.

3. Gamma-ray spectroscopy has the potential to predict many soil properties including nutrients (e.g. N). However, the technique is found to be limited to only the top soil to approximately 15 cm depth. Clay content is the primary soil property that can be determined directly. Other soil properties have indirect relations with radionuclides through clay content. Information thus obtained can be used for decisions on the management of the topsoil, e.g. for producing annual crops.
4. Both the full-spectrum analysis (FSA) and the energy-windows (EWs) methods can be used to relate radionuclide data with soil properties. The EWs method is a simpler method and relations can be developed using simple linear regression. The FSA methods with multivariate methods are less practical because a significant amount of pre-processing is needed and in this process, the correlations between radionuclides and soil properties may diminish.
5. Sensor data fusion or data integration significantly improves predictions of several soil properties, although not in all fields. Accuracies are better on clay than on sand. Proper selection of sensors for complementary fusion is crucial. Soil properties that show individual correlations with the outputs of EM38 and vis-NIR sensor (e.g. clay, sand, EC and pH) are predicted with a better accuracy than if they are predicted with either of the sensors. Therefore, data fusion is an effective approach to enhance the capabilities of currently available suite of soil sensors.
6. The commonly used EM38 can estimate soil texture and other soil properties. Combining the information from EM38 (ECa) with output of other sensors, e.g. vis-NIR spectrometer, improves the quality of soil sensing. This data fusion gives best results using partial least squares regression (PLSR), as compared to stepwise-multiple linear regression (SMLR) and principal components analysis combined with stepwise-multiple linear regression (PCA+SMLR). This result applies for most soil properties and indicates that PLSR has a better ability to deal with the multicollinearity among predictors of different sensors.
7. Geostatistical fusion is advantageous when covariates from all sensors have good correlation with the target variable (e.g. clay). Covariates having similar spatial structure as that of the target variable yield better variograms and cross-variograms. The prediction of clay content is improved after geostatistical fusion of data from the EM38, the vis-NIR spectrometer and the gamma-ray spectrometer. Geostatistical fusion improves predictions greatly when covariates show a good correlation with the target variable.

7.3. Outlook and recommendations

Precision agriculture is an important step for obtaining higher yields or reducing inputs in a sustainable way, as compared with conventional farming, where fields are considered as homogeneous units. However, soil sensing, sampling and laboratory analyses do not suffice when there is no reliable spatial information. There is a need to design and develop new sensing concepts with more direct sensing. Different on-line sensors, such as vis-NIR spectrometers, gamma-ray spectrometers, ground penetrating radar and EMI, will get more importance in near future. Predictive approaches need more refinement and reactive approaches also need to be employed. The encouraging results showed that data fusion is a way to enhance the performance of currently available sensors, but more effective methods are needed to deal with the data analysis. Following are recommendations for future research:

1. Continue the search for better understanding of the complex interaction between soil and sensor signals of different sensors.
2. Give sufficient attention to the development of sensors which can operate without extensive field calibration and focus on developing generic calibration.
3. Take up the challenges of studying economic and environmental benefits obtained using proximal soil sensors.
4. Develop better understanding of soil-sensor interaction for better interpretation of sensor data.
5. Explore new directions of the use of proximal soil sensors in the framework of precision agriculture and there is need for linking soil sensors to crop sensors in a "whole farm management approach".
6. Find answers to the question of how to expand the scale of vis-NIR spectroscopy and other sensing methods from one field to multiple fields, regional and national scales. Information based on multiple fields, on regional or national scale will greatly improve the quality of soil characterisation.
7. Take up the challenge of sensor data fusion for better decision support at the field scale and develop better data analysis methods for fusion, as this can enhance the quality of soil sensing. Improvement of methods in both classical statistics and geostatistics should be explored.
8. Give more focus to geostatistical methods for sensor data fusion. They will be more realistic in precision agriculture because soil properties always have a spatial structure in their distributions.
9. Include economic aspects in the development of sensors and methods of data fusion. Although certain data fusion techniques may be better in terms of better soil property estimation, these improvements may not counterbalance the direct (cost of sensor) and indirect (sampling, data processing) costs.

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Summary

Soil is a key resource that grows crops and holds plant, animal and human lives. This is our base resource that is becoming scarce due to degradation, salinity and sodicity problems and agricultural land is being lost in urbanisation and industrialisation to meet the needs of ever growing human population of the world. It is very crucial to manage this soil resource in an efficient and sustainable way to reap optimal yield of crops, reduce the amounts of inputs and protect it from degradation. For the better decision-making at the field level and for optimal use of crop inputs, such as fertilisers, seed, irrigation and chemicals, characterisation of different soil properties is very important.

Precision agriculture is a new and technological driven farm management system that aims to identify, analyse and manage variability in soil and crop attributes within fields for near-optimal profitability, sustainability, protection of land resources and safeguarding the environment. The main goal of precision agriculture is to manage and distribute farm inputs on a site-specific basis by customising the management for small areas within the field to maximise the profitability from agriculture. Therefore, before applying soil inputs, knowing about its physical and chemical properties is very vital. Laboratory testing of soil for different soil properties is used for years, which is a very expensive and laborious practice. Furthermore, the number of samples required for capturing within field variability necessary for implementing precision agriculture is not sufficient using manual sampling method. For this purpose, different remote and proximal soil sensors are available today that can scan entire fields and give detailed information on various physical, chemical, mechanical and biological soil properties. Soil sensors measure different physical attributes of soil that always exist and are directly and indirectly linked with different soil properties. Proximal soil sensors are advantageous because they can sense soil from very close distance or with the direct contact with it and therefore give better spatial resolution.

The first objective of this thesis was to evaluate different proximal soil sensors available today and to identify their capacity of quantifying soil properties. The second objective of this thesis was to enhance the usefulness of a single sensor system by multiple sensor data fusion that can improve the performance of currently available soil sensors when a single sensor does not function optimally due to certain set of soil and environmental constraints. Chapters 2, 3 and 4 deal with the first objective, whereas Chapters 5 and 6 deal with the second objective of this study. In Chapter 2, a comprehensive review was presented covering most commonly used proximal soil sensors. First, we divided proximal soil sensors into five major categories based on their sensing concepts. These categories include: reflectance based; conductivity, resistivity and permittivity based; radiation based; strength based and electrochemical based soil sensors. Under these categories the evaluated sensors include: visible-near infrared (vis-NIR) spectroscopy, mid-infrared (MIR) spectroscopy, electromagnetic induction (EMI), electrical resistivity (ER), ground penetrating radar (GPR), time-domain reflectometry (TDR), frequency-domain reflectometry (FDR), gamma-ray spectrometer, draught sensing, penetrometers, ion-selective electrodes (ISEs) and ion-sensitive field-effect transistors (ISFETs). To evaluate which sensor is needed for which soil property, we reviewed their sensing concepts, factors affecting their outputs, history of use in precision agriculture and directly and indirectly measured soil properties using a particular sensor. In this study, we concluded that proximal soil sensing technologies are very crucial for future farming and each sensor can give particular information on soil properties under varying conditions. For

example, strength sensors, ISEs, ISFETs, TDR and FDR sensors can individually give direct and quantitative information about a particular soil property. However, the vis-NIR spectroscopy has a great potential to estimate several soil physical, chemical and biological properties quantitatively directly and indirectly in precision agriculture. Similarly, gamma-ray spectroscopy is a relatively new sensing method and shows potential to measure soil texture and nutrients quantitatively. The EM38 is a widely used sensor in precision agriculture to estimate soil apparent electrical conductivity (ECa), which is an indirect indicator of clay, salinity and water content. These three sensors have been widely used and encapsulate the most part of literature in precision agricultural domain. Then some obvious advantages of these sensing technologies were also discussed, such as the role of sensors in fertiliser recommendation, modelling crop growth and yield, their use for site-specific tillage operations, carbon sequestration, the scope of sensor data fusion and its possible benefits, the accuracy of conventional soil sensing methods and its influence on sensor's output and the scope of future sensor development. Finally, based on the pertinent literature on these sensing technologies, their accuracy was assessed in laboratory, in-situ and on-line measuring platforms. Besides this, there were also limitations of this study where the benefits of these sensing methods have not been studied and were suggested as future research, such as environmental and economic gains of using these sensors, developing a better understanding of soil-sensor interaction, developing a better understanding of their sensing principles supported with their basic theories and focussing on theoretical or generic calibration of sensors.

In our second experiment (Chapter 3), we tested the robustness of vis-NIR reflectance models to predict workability related soil properties, such as texture and total organic carbon (TOC) and other common soil properties on a field scale using different types of modelling strategies in the Netherlands. The types of models included local models (LMs; models of individual fields), general models (GMs; models of combining equal proportions of samples from all fields), spiked models (SMs; using 10 samples from the target field and all samples from other fields) and true validation models (TVMs; calibration from four fields and validation in the remaining field). Focussing on tillage related soil properties, results revealed that LMs gave the best results, but a large number of samples has to be taken from each field that costs a lot of time and money. The general models showed variable accuracies for different sized models. Results showed that the general models with the highest number of samples showed better results than the ones with a lower number of samples. Models leaving an entire field out (TVMs) were cheap to make, but the worst predictions were obtained. In this case, there is a big risk of making big mistakes by wrong predictions. However, the SMs gave comparable results with that of the LMs. This implies that the SMs are very effective and are needed, which have the potential to predict workability related and other common soil properties with a limited number of samples in the target fields, although a generally lower accuracy has to be accepted. Expanding the scale of vis-NIR spectroscopy from a field to multiple fields can save expense and time greatly with a little loss of accuracy of soil property predictions.

In our next experiment (Chapter 4), we tested the potential of gamma-ray spectroscopy in two fields (Fields 1 and 2 mentioned in Chapter 3) to predict soil properties in two depths: the top 0-15 cm and the 15-30 cm. As the data analysis methods can significantly affect the

accuracy of predictions, we compared two data analysis methods used in gamma-ray spectroscopy: energy-windows method (EWs) and full-spectrum analysis method (FSA). It is obvious that in the EWs method limited portion of energy spectrum takes part in the analysis, whereas the FSA method considers the entire gamma-ray energy spectrum. From this experiment, we found that gamma-ray spectroscopy can measure and predict clay, pH, total nitrogen (TN) and TOC successfully (R^2 ~ 0.50) in the top 0-15 cm soil depth. Better predictions in the top soil indicate that emission of gamma rays from the top a few cm depth is more than the subsoil. With increasing soil depth, the proportion of detected gamma-rays is reduced. This means that gamma-ray spectroscopy can generally benefit soil characterisation for annual crops where the condition of the seedbed is important. Both the EWs and FSA methods yielded comparable results of soil property predictions. This study concluded that gamma-ray spectroscopy is a promising technique in precision agriculture and can predict several soil properties. Furthermore, the EWs method can establish relations between radionuclide data and soil properties as accurate as the FSA method can do.

In our next experiment (Chapter 5), we explored the potential of sensor data fusion that is a new and future topic of research. A single sensor cannot function optimally when certain environmental and soil factors affect sensor's output in a similar way. Data fusion of different sensors may be a good way to reflect better accuracy and increase the significance of proximal soil sensors already used in precision agriculture. Therefore, the main aim of data fusion is to measure the target soil property with a better quality and reliability by getting complementary information from different sensors. In this experiment, we used two soil sensors for data fusion: EM38 and vis-NIR spectrometer, in three different fields in the Netherlands. We predicted the same soil properties used in previous experiments; for example, clay, silt, sand, EC, pH, TOC and TN. Data fusion improved the accuracy of predictions of clay, silt, sand, EC and pH significantly, although not in all fields. Better results were found in a clayey fields and worse in a sandy field. The prediction accuracy was greatly improved when both sensors showed a good correlation with a certain soil property. Therefore, the performance of data fusion is largely affected by the type of sensors used for data fusion. Promising results of this study concluded that sensor data fusion can potentially give many benefits, such as better accuracy, extended attribute coverage and complementary information on certain soil properties. Despite these benefits of data fusion the technique may hamper due to difficulty in handling large volumes of data from multiple sensors, lack of accuracies in positioning systems and complex data analysis methods. The economic concerns have also not been proved for data fusion. Furthermore, we used and compared three data analysis methods for fusion: stepwise multiple linear regression (SMLR), partial least square regression (PLSR) and principal components analysis combined with stepwise multiple linear regression (PCA+SMLR). All methods yielded comparable results, but PLSR produced slightly better results. This implies that PLSR has a better ability to deal with the multicollinearity among the predictor variables of multiple sensors. This is also because different statistical methods have different built-in assumptions, background theory and procedures of analysis. Many new and sophisticated software systems can be attempted; however, simpler methods are better and should be preferred for data analysis. We concluded that with the available suite of sensors, sensor data fusion is a viable option to enhance the quality of prediction of several soil properties.

In our next experiment (Chapter 6), we attempted geostatistical data fusion to estimate clay content in a small agricultural field. When the measured soil properties have good spatial correlation then geostatistical methods can give better estimates and should be preferred on classical statistical methods. But, if there is no spatial structure in the distribution of soil properties, the classical statistical methods are preferred. Ordinary kriging is an unbiased interpolation methods to map a target variable (here clay content) when a sufficient number of soil samples (e.g. >50) are taken from the field. The estimate of clay content can be improved if we use different covariates from different sensors that have good correlations with clay content and also have spatial structures. In this experiment we used four covariates: ^{232}Th (from gamma-ray spectrometer), ECa (horizontal dipole reading of EM38), W388 and W1197 (two wavelengths from vis-NIR spectrometer). These covariates were measured from different locations in the field. For example, ^{232}Th was measured real-time using transects and the rest of covariates were measured from clay sampling locations (72 locations in the field) only. We used univariate geostatistics, such as ordinary kriging (OK) for only clay mapping and multivariate geostatistics, such as universal kriging (UK) when clay was linked with ^{232}Th covariate, co-kriging (CK) to incorporate ECa, W388 and W1197 covariates with clay content and finally universal co-kriging (UCK) to combine all these covariates with clay content. Cross-validation results indicated that geostatistical data fusion (UCK) from the covariates of these sensors greatly improved the quality of prediction and R^2 value increased from 0.65 to 0.87. Similarly, the RMSE was reduced from 0.80 (in OK) to 0.47 in the UCK, which is almost the half. Geostatistical data fusion is also important because the number of soil samples taken for analysis is not always enough to capture variability at a scale at which soil properties vary in space. In this case, if soil properties have good correlations with the ancillary data of proximal sensors then the variograms of densely measured covariates can approximate the scale of variation in soil properties that can further help reduce the number of soil samples. This study suggests that geostatistical data fusion from proximal soil sensors can improve the quality of clay prediction reasonably, although the diffidence is not dramatically large in this study. This is attributed to somewhat different spatial structures of covariates from the target variable.

The results from all experimental chapters have been discussed in a broader sense in the general discussion (Chapter 7). We summarised main conclusions, suggested future directions of proximal soil sensors and identified the need for new sensors development. The approaches used in this thesis will help the reader to identify a proper sensor to measure a particular soil property. This work can also serve as a step forward for enhancing the performance of currently available sensors in the form of sensor data fusion. Finally, sensor data fusion will open a new direction of research in precision agriculture. In future, more research will be carried out on various aspects of sensor data fusion including studying the economic feasibility of fusion methods.

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Samenvatting

De bodem is de belangrijkste bron voor de productie van voedsel voor mens en dier maar wordt bedreigd door diverse vormen van degradatie. Het oppervlak land beschikbaar voor landbouw wordt steeds kleiner door urbanisatie en industrialisatie, terwijl een groeiende wereldpopulatie moet worden gevoed. Het is daarom cruciaal dat deze bron zo efficiënt mogelijk wordt gebruikt op duurzame wijze. Om dit te bereiken moet er optimaal gebruik gemaakt worden van inputs zoals (kunst)mest, zaad, chemische middelen, irrigatie. Hierbij is kennis van de bodemeigenschappen van grote waarde.

Precisielandbouw is een nieuw systeem van voedselproductie gebaseerd op nieuwe technologieën met als doel en middel om de variabiliteit van bodem en gewas binnen een perceel zo goed mogelijk te meten, te analyseren en te gebruiken als basis voor beslissingen voor het management van de bodem teneinde een maximale opbrengst te krijgen waarbij zowel deze natuurlijke hulpbron als de omgeving worden ontzien. Hoofddoel van precisielandbouw is om inputs zodanig te beheren, toe te passen en te verdelen zodat er maximaal gebruik kan worden gemaakt van de potentie van alle segmenten van een veld. Kennis van de fysische en chemische eigenschappen van de bodem is daarom van vitaal belang, maar de gangbare methode van bemonsteren en analyseren van grond in het laboratorium is kostbaar en tijdrovend. Daarnaast kan bemonsteren met de hand bijna nooit voldoende monsters opleveren om betrouwbaar de ruimtelijke variabiliteit binnen een veld te bepalen.

Op dit moment zijn er verscheidene sensoren ontwikkeld en beschikbaar die van grote (remote) of kleine afstand (proximal) veel gedetailleerde informatie kunnen geven van een veld, zowel van fysische en chemische, maar ook mechanische en biologische bodemeigenschappen. Bodemsensors meten echter een combinatie van verschillende eigenschappen, die op hun beurt weer direct of indirect gekoppeld kunnen worden aan andere eigenschappen die van belang zijn voor bodem management. Sensors die van korte afstand meten hebben het voordeel dat ze een veel betere ruimtelijke resolutie hebben en dus betere informatie verschaffen dan “remote sensing”.

Het eerste doel van dit proefschrift is om een evaluatie te geven van de verschillende ‘proximal’ bodemsensors die op dit moment beschikbaar zijn en een indicatie te geven van hun mogelijkheden om bodemeigenschappen te kwantificeren. Het tweede doel is om te onderzoeken of het nut van één enkel sensorsysteem kan worden verbeterd door dit te koppelen aan het gebruik van meerdere systemen die op een ander principe zijn gebaseerd. De hypothese is dat een enkel systeem niet optimaal kan werken door de belemmeringen die aan een meetsysteem ten grondslag liggen.

In dit proefschrift behandelen hoofdstukken 2, 3 en 4 de eerste doelstelling, en hoofdstukken 5 en 6 de tweede. In hoofdstuk 2 wordt een uitgebreid overzicht gegeven

van de meest gebruikte proximal bodem sensoren. De sensoren zijn in vijf categorieën verdeeld gebaseerd op het meetprincipe. Deze principes zijn: reflectie, geleidbaarheid en weerstand, straling, sterkte en electrochemisch. Een vijtiental sensors zijn geëvalueerd met betrekking tot hun recente gebruik binnen precisielandbouw, met betrekking tot het meetprincipe, en tot factoren die de output van de sensor beïnvloeden, dit om de toepasbaarheid bij verschillende bodemeigenschappen te bepalen. De conclusie van deze studie was dat vooral de proximal sensoren specifieke informatie van de bodem kan leveren onder diverse omstandigheden en dat zij daarmee cruciaal zijn voor toekomstig gebruik in de landbouw.

Sensors zijn ook beoordeeld op hun toepassing zoals bijvoorbeeld advies voor kunstmestgiften, modelleren van gewasgroei en opbrengstvoorspelling, voor plaatsspecifieke grondbewerking, en voor opslag van koolstof in de grond . Ook is gekeken naar de mogelijkheden voor combineren van de sensors (fusion) nu en mogelijk in de toekomst. Gebaseerd op een groot aantal gegevens in de literatuur, zijn de verschillen in nauwkeurigheid en reproduceerbaarheid (betrouwbaarheid) tussen deze sensors en conventionele methoden in kaart gebracht.

In hoofdstuk 3 is verslag gedaan va het testen van de robuustheid van vis-NiR reflectie modellen om de bewerkbaarheid van grond te voorspellen, gebaseerd op textuur, totale hoeveelheid C en andere eigenschappen, dit alles op perceelsniveau door gebruik te maken van een aantal modellen die de ruimtelijke spreiding van de reflectiemetingen analyseren (local, spiked, general en true validation models). De zgn. local models gaven de beste resultaten maar vereiden een groot aantal monsters (data) per veld. De resultaten van de spiked models waren bijna vergelijkbaar met die van de local models en konden worden verkregen met veel minder monsters per perceel. Ook als meer percelen in de analyse van de vis-NIR spectroscopie worden meegenomen, kan de nauwkeurigheid van de voorspellingen sterk verbeterd worden.

Een proef met gamma-straling spectroscopie is beschreven in hoofdstuk 4 . Hier werd gekeken naar de bepaling van bodemeigenschappen over twee dieptes, 0-15 en 15-30 cm. De energie-spectra die worden gemeten met deze sensor zijn op verschillende manieren (gehele spectrum en “windows” ofwel specifieke ranges in het spectrum) geanalyseerd. De proeven toonden aan dat deze sensor technologie klei, pH, totaal stikstof en totaal koolstof goed kan bepalen in de bovenste 15 cm. De emissie van gamma straling uit diepere lagen is duidelijk minder waardoor deze sensor vooral geschikt lijkt om de eigenschappen van een zaaibed te bepalen. De resultaten van de verschillende analyse methoden ontliepen elkaar zeer weinig waardoor de windows methode (is simpeler) aantrekkelijker lijkt.

In hoofdstuk 5 zijn de mogelijkheden van sensor-fusie bekeken. Sensors kunnen worden beïnvloed door specifieke bodem en omgevings eigenschappen, maar deze zijn niet voor alles sensors gelijk. Hierdoor kan een fusie van de resultaten van verschillende soorten sensoren wellicht tot een betere nauwkeurigheid leiden om daarmee tot een effectiever gebruik van de sensoren in precisielandbouw te komen. Twee sensoren werden gebruikt in een experiment: de EM38 voor de bepaling van de electromagnetische inductie, en de vis-NIR spectrometer. Dit werd gedaan op drie verschillende percelen in Nederland. Klei, silt, zand, EC, pH, totaal-koolstof (TOC) en totaal-stikstof (TN) werden gekwantificeerd met beide methoden. Het bleek dat fusie een verbetering van de nauwkeurigheid van de voorspellingen gaf, behalve bij TOC en TN. Resultaten waren ook beter in een perceel met een zwaardere grond dan op een zandgrond. Het blijkt wel dat de kwaliteit van data fusie sterk afhangt van het type sensor. Er zijn duidelijk voordelen aan te wijzen (naast de betere nauwkeurigheid ook een grotere range van bodem eigenschappen), maar het is niet eenvoudig om de grote hoeveelheid data die door de sensoren wordt gegenereerd, te analyseren, en afwijkingen in plaatsbepaling in het perceel van de sensoren kunnen de resultaten negatief beïnvloeden. Er is ook nog niet gekeken naar de (mogelijke) economische voordelen van datafusie. Een drietal analysemethodes is uitgetest in dit experiment , waarbij de "partial least square regression" de beste resultaten gaf. Het is echter zaak om uit de veelheid van statistische methoden (en de beschikbare software) goede keuzes te maken en te trachten de analyses te versimpelen. De conclusie is dat data fusie een reële mogelijkheid biedt om de voorspellingskwaliteit te verbeteren.

In hoofdstuk 6 is beschreven hoe met behulp van geostatistiek tot een fusie van data kan worden gekomen. Dit is gedaan door het gehalte klei te schatten op een relatief klein perceel. Als de gemeten bodemeigenschappen een goede ruimtelijke correlatie hebben, dan kunnen geostatistische methoden betere schattingen geven en genieten de voorkeur boven klassieke statistische methoden. Als er geen ruimtelijk correlatie is, dan hebben de klassieke methoden de voorkeur. "Kriging" is een interpolatie methode die een bepaalde variabele (in dit gevall kleigehalte) in kaart kan brengen als er een voldoende groot aantal monsters van een veld (in dit geval > 50) wordt genomen. De schatting van het kleigehalte kan worden verbeterd als verschillende covarianten van verschillende sensors die allen goede correlaties hebben met klei én een goede ruimtelijke structuur. In dit experiment werden vier covarianten gebruikt, verkregen bij metingen met de gamma-ray en de vis-NIR spectroscopie, en de EM38 (EC) inductie. Diverse geostatistische methoden zijn hier toegepast waaruit bleek dat "universal co-kriging" de beste resultaten gaf, d.w.z. de RMSE (root mean square error) was hier het laagst. De resultaten geven aan dat geostatistische fusie van de data verkregen met bovengenoemde methoden de schatting van het kleigehalte kan verbeteren, maar een

voorwaarde is dat de ruimtelijke structuur duidelijk moet zijn en niet te veel moet verschillen tussen de metingen met de gebruikte sensors.

Een algemene discussie is gegeven is hoofdstuk 7 waar de resultaten worden gesteld in het licht van mogelijke nieuwe ontwikkelingen. Het geeft aan welke criteria kunnen worden gebruikt om een geschikte sensor te kiezen. De conclusie die getrokken kan worden is dat sensor data fusie een nieuwe impuls kan geven in de verhoging van de wetenschappelijke en economische waarde van het gebruik van bodemsensors.

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خلاصہ

زمین کے اتصالی حساسے اور دقیق زراعت کے لئے حسی مواد کا اختلاط

حافظ سلطان محمود

جولائی ۴ ، ۲۰۱۳

واخننگن، دی نیدرلینڈز (ہالینڈ)

زمین ایک اہم وسیلہ ہے جو فصلیں اگاتا ہے اور پودوں، جانوروں اور انسانوں کی زندگی کا ضامن ہے۔ یہ ہمارا بنیادی وسیلہ ہے جو توڑ پھوڑ، سیم و تھور اور سوڈے کے مسائل کی وجہ سے نایاب ہو رہا ہے اور زرعی زمین دنیا کی کہیں تیزی سے بڑھتی ہوئی آبادی کے لئے شہری اور صنعتی سہولیات میسر کرنے کیے لئے ضائع ہو رہی ہے۔ زمین کے اس وسیلے کا ایک مناسب اور پائیدار انتظام بہت ضروری ہے تاکہ فصلوں کی زیادہ سے زیادہ پیداوار لی جائے، داخلی مواد کو کم کیا جائے اور اسے توڑ پھوڑ سے بچایا جائے۔ کھیت کی سطح پر اچھی فیصلہ سازی اور داخلی مواد جیسا کہ کھادیں، بیج، آبپاشی اور کیمیائی مادوں کے بہترین استعمال کے لئے زمین کے مختلف خواص کی شناخت بہت ضروری ہے۔

دقیق زراعت ایک نئی اور ٹیکنالوجی سے بھرپور کھیتوں کی تدبیر کا نظام ہے جس کا مقصد زمین اور فصلوں کے مختلف خواص کی ناہمواری کو شناخت کرنا، تجزیہ کرنا اور اس کا انتظام کرنا ہے تاکہ تقریباً زیادہ سے زیادہ منافع بخشی، پائیداری اور زمینی اور ماحولیاتی وسائل کا تحفظ کیا جاسکے۔ دقیق زراعت کا مرکزی مقصد کھیت میں داخلی مواد کا انتظام اور اسکی مکانی ضرورت کے مطابق تقسیم ہے جو کہ زیادہ سے زیادہ منافع لینے کے لئے کھیت کو چھوٹے چھوٹے ٹکڑوں میں تقسیم کر کے کی جاتی ہے۔ اس لئے زمین میں داخلی مواد ڈالنے سے پہلے اس کے طبعی اور کیمیائی خواص کے بارے میں علم ہونا انتہائی ضروری ہے۔ زمین کا مختلف خواص کے لئے لیبارٹری میں ٹیسٹ کرنا کئی سالوں سے ہو رہا ہے جو ایک مہنگا اور مشقت طلب کام ہے۔ علاوہ ازیں، کھیت کے اندر دقیق زراعت کے نفاذ کے لئے مطلوبہ ناہمواری کو گرفت میں کرنے کے لئے ہاتھوں سے مٹی یا زمین کے نمونے لینا ناکافی ہیں۔ اس مقصد کے لئے آج کل مختلف اتصالی اور بعیدی حساسے موجود ہیں جو سارے کھیتوں کا مطالعہ کر سکتے ہیں اور زمین کے مختلف طبعی، کیمیائی، میکانی اور حیاتیاتی خواص کے بارے میں جامع معلومات دے سکتے ہیں۔ مٹی کے حساسے زمین کے مختلف عناصر کی پیائش کرتے ہیں جو ہمیشہ موجود ہوتے ہیں اور بالواسطہ یا بلاواسطہ زمین کے مختلف خواص کے ساتھ منسلک ہوتے ہیں۔ زمین کے اتصالی حساسے زیادہ فائدہ مند ہیں کیونکہ یہ زمین کو بڑے قریب سے یا چھو کر محسوس کر سکتے ہیں اور اس طرح بہتر مکانی پیائش دے سکتے ہیں۔

اس مقالے کا پہلا مقصد مختلف موجودہ اتصالی حساسوں کا تجزیہ کرنا اور زمین کے مختلف خواص معلوم کرنے میں انکی قابلیت جانچنا تھا۔ اس مقالے کا دوسرا مقصد ایک حساسے کی مفادیت کو مختلف حساسوں کے حسی مواد کے اختلاط سے بڑھانا تھا جو موجودہ حساسوں کی کارکردگی کو بڑھانے کا ایک طریقہ ہے جب ایک حساسہ مختلف ماحولیاتی اثرات کی بدولت صحیح طور پر کام نہیں کر سکتا۔ باب ۲ ، ۳ اور ۴ اس مطالعہ کے پہلے مقصد کے بارے میں ہے جبکہ باب ۵ اور ۶ دوسرے مقصد کے بارے میں ہے۔ باب ۲ میں عام طور پر استعمال ہونے والے اتصالی حساسوں کا جامع تجزیہ اور تنقید پیش کی گئی ہے۔ پہلے ہم نے اتصالی حساسوں کو ان کے حسی اصولوں کی بنیاد پر پانچ بڑے گروہوں میں تقسیم کیا۔ ان پانچ گروہوں میں انعکاس کی بنیاد ؛ایصالیت، مزاحمت اور انجزاب کی بنیاد؛ شعاؤں

کی بنیاد؛ طاقت کی بنیاد اور برقی کیمیائی بنیاد والے شامل ہیں۔ ان گروہوں میں جن حساسوں کا تجزیہ کیا گیا ان میں مرئی اور قصیر زیر سرخ طیف پیمائی (وزیبل اور نیر انفراریڈ سپیکٹروسکوپی)، وسطی زیر سرخ طیف پیمائی (مڈ انفراریڈ سپیکٹروسکوپی)، برقی مقناطیسی امالہ (الیکٹرومیگنیٹک انڈکشن)، برقی مزاحمت (الیکٹریکل ریزسٹیویٹی)، زمین زیرک ریڈار (گراؤنڈ پینیٹریٹنگ ریڈار)، ٹائم ڈومین انعکاس پیمائی، فریکونسی ڈومین انعکاس پیمائی، گیمارے طیف پیما، کھچاؤ محسوس کرنا (ڈرافٹ)، نفوذ پیما (پینیٹرومیٹرز)، منتخب آئن کے برقیرے (آئن سیلیکٹو الیکٹروڈ) اور مخصوص آئن کے ٹرانزسٹر (آئن سینسیٹو فیلڈ افیکٹ ٹرانزسٹرز) شامل ہیں۔ یہ تجزیہ کرنے کے لئے کہ کونسا حساسہ زمین کی کس خاصیت کے لئے موزوں ہے، ہم نے ان کے بنیادی اصولوں، ان کے سگنل کو متاثر کرنے والے عناصر، دقیق زراعت میں ان کے استعمال کی تاریخ اور بالواسطہ اور بلاواسطہ معلوم کئے جانے والے خواص کا جائزہ پیش کیا۔ اس مطالعہ میں ہم نے یہ نتیجہ اخذ کیا کہ اتصالی حساسے مستقبل کی زراعت میں بہت اہم ہیں اور ہر حساسہ مختلف حالات میں زمین کے خواص پر مخصوص معلومات دے سکتا ہے۔ مثال کے طور پر، طاقت کی پیائش والے حساسے، منتخب آئن کے برقیرے، مخصوص آئن کے ٹرانزسٹر، ٹائم ڈومین انعکاس پیما اور فریکونسی ڈومین انعکاس پیما انفرادی طور پر بلاواسطہ طور پر زمین کے کسی مخصوص خواص کے بارے میں ہندسی اور مقداری معلومات دے سکتے ہیں۔ تاہم مرئی اور قصیر زیر سرخ طیف پیمائی دقیق زراعت میں زمین کے کئی طبعی، کیمیائی اور حیاتیاتی خواص کو بالواسطہ اور بلاواسطہ معلوم کرنے کی بڑی صلاحیت رکھتی ہے۔ اسی طرح گیمارے طیف پیمائی نسبتاً ایک نیا طریقہ ہے اور زمین کی بناوٹ (ٹیکسچر) اور نامیاتی مواد کو معلوم کرنے کی بہترین صلاحیت رکھتی ہے۔ ای ایم۔۳۸ دقیق زراعت میں بہت زیادہ استعمال ہونے والا حساسہ ہے جو زمین کی برقی ایصالیت کی پیائش کرتا ہے اور زمین میں موجود میرا ذرات، نمکیات اور پانی کا اندازہ لگانے کا ایک بالواسطہ پیمانہ ہے۔ یہ تین حساسے بہت زیادہ استعمال ہوتے ہیں اور دقیق زراعت کا زیادہ لٹریچر انہی پر مشتمل ہے۔ پھر ان حساسوں کے قابل ذکر فوائد جیسا کہ کھاد کے استعمال میں ان کا کردار، فصل کی نشوونما اور پیداوار کے ماڈل بنانے میں ان کا کردار، زمین کی تیاری میں ان کا استعمال، کاربن کے اخراج کو روکنے میں ان کا کردار، حسی مواد کے اختلاط کے ممکنات اور اس کے ممکنہ فوائد، زمین کو محسوس کرنے کے روائتی طریقوں کے صحیح ہونے کا معیار اور ان کا حساسوں کے حاصلات پر اثرات اور مستقبل میں نئے حساسوں کی بناوٹ کے ممکنات کو بیان کیا گیا۔ آخر میں ان حسی ٹیکنالوجیز کے متعلقہ لٹریچر کی بنیاد پر ان کی درستگی کی جانچ لیبارٹری، فی محلہ کھیت میں اور آن لائن کی گئی۔ اس کے علاوہ اس مطالعہ میں کچھ کمی بھی ہے جہاں ان حساسوں کے فوائد کا مطالعہ نہیں کیا گیا اور انہیں مستقبل کے مطالعہ کے لئے تجویز کیا گیا ہے جیسا کہ ان حساسوں کے استعمال سے ماحولیاتی اور معاشی فوائد کی پیائش، زمین اور حساسے کے درمیان ایک اچھے ارتباط کا قیام، ان حساسوں کے محسوس کرنے کے قوانین کو تھیوری کے ساتھ بہتر انداز میں سمجھنا اور ان حساسوں کی تھیوریٹکل کیلیبریشن کو مد نظر رکھنا اور اس پر زور دینا ہے۔

ہمارے دوسرے تجربے میں (باب ۳) ہم نے مرئی اور قصیر زیر سرخ طیف پیمائی کو زمین کی تیاری سے متعلق خواص معلوم کرنے کے لیے اس کی صلاحیت اور طاقت کا معائنہ اس کے مختلف قسم کے ماڈلوں کو استعمال کرتے ہوئے نیدر لینڈز میں کیا، جیسا کہ فی محلہ کھیت میں ٹیکسچر، مجموعی کاربن اور دوسری متعلقہ خواص کو معلوم کرنا۔ ماڈلوں کی اقسام میں لوکل ماڈلز (انفرادی کھیت کے ماڈلز)، جنرل ماڈلز (تمام کھیتوں سے برابر تناسب میں نمونے لے کر ملائے گئے ماڈلز)، سپائکڈ ماڈلز (۱۰ نمونے متعلقہ کھیت سے اور سارے نمونے دوسرے کھیتوں سے لے کر بنائے گئے ماڈلز) اور حقیقی ٹیسٹ ماڈلز (چار کھیتوں کے نمونوں سے کیلیبریشن ماڈل بنا کر پانچویں کھیت میں ٹیسٹ کرنا)۔ زمین کی تیاری سے متعلقہ خواص کو مد نظر رکھتے ہوئے، نتائج یہ ظاہر کرتے ہیں کہ لوکل ماڈلز سب سے بہتر نتائج دیتے ہیں لیکن ہر کھیت سے بہت بڑی تعداد میں نمونے لینے پڑتے ہیں جس کے لیے زیادہ رقم اور وقت درکار ہے۔ مختلف تناسب کے نمونوں کے جنرل ماڈلز ملی جلی درستگی ظاہر کرتے ہیں۔ نتائج یہ ظاہر کرتے ہیں کہ نمونوں کی زیادہ تعداد والے جنرل ماڈلز کم نمونوں والے ماڈلز کی نسبت زیادہ اچھے نتائج دیتے ہیں۔ حقیقی ٹیسٹ ماڈلز بنانے میں تو بڑے سستے ہیں، لیکن برے نتائج ظاہر کرتے ہیں۔ اس ماڈلز سے پیشگوئیاں کرتے ہوئے بڑی غلطیاں سرزد ہونے کا بڑا خطرہ ہے۔ تاہم سپائکڈ ماڈلز نے لوکل ماڈلز کے مقابلے میں تقریباً برابر نتائج دیے۔ اس سے ہم یہ نتیجہ اخذ کرتے ہیں کہ سپائکڈ ماڈلز بڑے مؤثر اور ضروری ہیں جو متعلقہ کھیت میں زمین کی تیاری سے متعلقہ اور دوسرے خواص کو زمین کے محدود نمونوں سے پیشگوئی کے لئے بڑی صلاحیت رکھتے ہیں اگرچہ تھوڑی سی کم درستگی تسلیم کرنی پڑتی ہے۔ مرئی اور قصیر زیر سرخ طیف پیمائی کو ایک کھیت کی سطح سے زیادہ کھیتوں تک پھیلانے سے اور زمین کے خواص کی پیشگوئی کی درستگی میں تھوڑی سی کمی سے رقم اور وقت کو کافی حد تک بچایا جاسکتا ہے۔

اگلے تجربے میں (باب ۴) ہم نے گیما طیف پیمائی کا زمین کے خواص کی پیشگوئی کے لئے دو کھیتوں (کھیت ۱ اور کھیت ۲ جیسا کہ باب ۳ میں بیان کیا گیا ہے) میں اور دو گہرائیوں تک معائنہ کیا: بالائی ۰۔۱۵ سینٹی میٹر تہہ اور زیریں ۱۵۔۳۰ سینٹی میٹر تہہ۔ کیونکہ مواد کے تجزیے کے طریقے واضح طور پر پیشگوئیوں کی درستگی کو متاثر کر سکتے ہیں اس لئے ہم نے مواد کے تجزیے کے دو طریقوں کو مقابلتاً جانچا جو کہ گیمارے طیف پیمائی میں استعمال ہوتے ہیں: توانائی پٹی والا طریقہ اور مکمل منشور والا طریقہ۔ یہ واضح ہے کہ توانائی پٹی والے طریقے میں منشور کا ایک محدود سا حصہ استعمال ہوتا ہے جبکہ مکمل منشور والے طریقے میں سارا گیمارے منشور حصہ لیتا ہے۔ اس تجربے سے ہم نے نتیجہ اخذ کیا کہ گیمارے طیف پیمائی زمین کی بالائی تہہ (۰۔۱۵ سم) میں میرا ذرات کی مقدار، پی ایچ، کل نائٹروجن اور کل نامیاتی کاربن کو کامیابی کے ساتھ معلوم کر سکتی ہے ($R^2 = 0.50$)۔ بالائی زمین میں بہتر پیشگوئیاں یہ ظاہر کرتی ہیں کہ زمین کی چند سینٹی میٹر بالائی تہہ سے گیما شعاعوں کا اخراج زیریں زمین سے زیادہ ہے۔ زمین کی گہرائی بڑھنے سے گیما شعاعوں کو محسوس کرنے کا تناسب کم ہو جاتا ہے۔ اس کا مطلب ہے کہ گیمارے طیف پیمائی عام طور پر سالانہ فصلوں کے لئے زمین کی شناخت

کے لئے زیادہ مفید ہے جہاں زمین کی بیج ڈالنے والی تہہ زیادہ اہم ہوتی ہے۔ دونوں طریقوں، توانائی پٹی والا طریقہ اور مکمل منشور والا طریقہ، نے مقابلتاً برابر زمین کے خواص کی پیشگوئیاں دیں۔ اس مطالعہ سے یہ نتیجہ نکلتا ہے کہ گیمارے طیف پیمائی دقیق زراعت میں ایک پسندیدہ طریقہ ہے جو زمین کے پیشتر خواص کی پیشگوئی کر سکتا ہے۔ علاوہ ازیں توانائی پٹی والا طریقہ بھی زمین میں موجود تابکار مواد اور زمین کے خواص کے درمیان اتنے درست ارتباط پیدا کر سکتا ہے جتنا کہ مکمل منشور وال طریقہ کر سکتا ہے۔

ہمارے اگلے تجربے میں (باب ۵)، ہم نے حسی مواد کے اختلاط کے ممکنات کو دریافت کیا جو کہ ایک نیا اور مستقبل کی تحقیق کا عنوان ہے۔ ایک حساسہ بہترین طریقے سے عمل نہیں کر سکتا جب چند مخصوص ماحولیاتی اور زمینی عناصر حساسے کے حاصلات کو متاثر کرتے ہیں اور وہ ایک ہی طرح کے حاصلات پیش کرتا ہے۔ مختلف حساسوں کی معلومات کا اختلاط بہتر درستگی کے لئے ایک اچھا طریقہ ہو سکتا ہے اور دقیق زراعت میں استعمال ہونے والے موجودہ حساسوں کی اہمیت کو بڑھا سکتا ہے۔ اس لئے مواد کے اختلاط کا بڑا مقصد یہ ہے کہ زمین کی مطلوبہ خاصیت کو بہتر کوالٹی اور پائیداری سے معلوم کیا جائے جو مختلف حساسوں کی باہمی معلومات سے حاصل کیا جاتا ہے۔ اس تجربے میں ہم نے دو حساسوں، ای ایم-۳۸ اور مرئی اور قصیر زیر سرخ طیف پیما، کے مواد کا اختلاط ہالینڈ میں تین مختلف کھیتوں میں کیا۔ ہم نے زمین کے انہی خواص کی پیشگوئی کی جو پچھلے تجربوں میں کی گئی تھیں مثال کے طور پر میر اذرات کی مقدار، سلٹ کے ذرات کی مقدار، ریت کے ذرات کی مقدار، برقی ایصالیت، پی ایچ، کل نامیاتی کاربن اور کل نائٹروجن۔ مواد کے اختلاط سے میر اذرات کی مقدار، سلٹ کے ذرات کی مقدار، ریت کے ذرات کی مقدار، برقی ایصالیت اور پی ایچ کی پیشگوئیاں واضح طور پر بہتر ہوئیں اگرچہ یہ پیشگوئیاں تمام کھیتوں میں بہتر نہیں تھیں ۔ میر اکھیت میں بہتر نتائج آئے جبکہ ریتلے کھیت میں کم بہتر نتائج آئے ۔ جب دونوں حساسوں نے کسی مخصوص خاصیت کے ساتھ انفرادی طور پر اچھا ارتباط ظاہر کیا تو اختلاط سے پیشگوئیوں کی درستگی بڑی حد تک بہتر ہوئی۔ اس لئے مواد کے اختلاط کی کارکردگی بڑی حد تک استعمال ہونے والے حساسوں پر اثر انداز ہوتی ہے۔ اس مطالعے کے حوصلہ افزا نتائج سے یہ نتیجہ اخذ کیا گیا کہ حسی مواد کا اختلاط ممکنہ طور پر بڑے فوائد دے سکتا ہے جیسا کہ بہتر درستگی، زیادہ خواص کا احاطہ اور مخصوص خواص پر باہمی معلومات۔ مواد کے اختلاط کے ان فوائد کے باوجود یہ تکنیک مختلف حساسوں کے مواد کی زیادہ مقدار کے بندوبست، پوزیشن کی درستگی میں خامی اور مواد کے تجزیے کے پیچیدہ طریقوں سے رکاوٹ کا شکار ہو سکتی ہے۔ حسی مواد کے اختلاط کے معاشی فوائد بھی ثابت شدہ نہیں ہیں۔ اس کے علاوہ ہم نے مواد کے اختلاط کے تجزیے کے لئے تین طریقے استعمال کیے: سلسلہ وار ملٹیپل لینیر ریگریشن، پارشل لیسٹ سقیر ڈ ریگریشن اور پرنسپل کمپوننٹ انالائسس کو سلسلہ وار ملٹیپل لینیر ریگریشن کے ساتھ ملا کر۔ تمام طریقوں سے برابر نتائج حاصل ہوئے لیکن پارشل لیسٹ سقیر ڈ ریگریشن سے تھوڑے سے اچھے نتائج حاصل ہوئے۔ اس سے یہ دلیل لی جاتی ہے کہ پارشل لیسٹ سقیر ڈ ریگریشن مختلف حساسوں کے پیشگوئی والے متغیرات میں موجود مماثلت

کو حل کرنے کی بہتر صلاحیت رکھتی ہے۔ اس کی وجہ یہ بھی ہے کہ شماریات کے مختلف طریقوں کے مختلف ابتدائی مفروضے ہوتے ہیں، ان کی تھیوری مختلف ہوتی ہے اور ان کے استعمال کے طریقے مختلف ہوتے ہیں۔ بہت سے نئے اور بہترین سوفٹ ویئر استعمال کیے جاسکتے ہیں لیکن تجزیہ کے لیے ہمیشہ سادہ طریقوں کو ترجیح دینی چاہیے۔ ہم نے یہ نتیجہ اخذ کیا کہ موجودہ حساسوں کی پیشگوئی کرنے کی صلاحیت اور کوالٹی کو بڑھانے کے لیے حسی مواد کا اختلاط نہایت اہم ذریعہ ہے۔

ہمارے اگلے تجربے میں (باب ۶) ہم نے حسی مواد کے اختلاط کے لیے ارضی شماریات کا طریقہ استعمال کیا اور ایک چھوٹے سے زرعی کھیت میں میر اذرات کی مقدار کی پیائش کی۔ جب پیائش کیے گئے زمینی خواص کی اچھی باہمی مکانی ارتباط ہو تو زمینی شماریات اچھے نتائج دے سکتی ہے اور اسے روایتی شماریات کے طریقوں پر ترجیح دینی چاہیے۔ لیکن اگر زمینی خواص کی مکانی ساخت میں کوئی ارتباط نہ ہو تو روایتی شماریات کے طریقوں کو ترجیح دینی چاہیے۔ عام کریگنگ کا طریقہ ایک متوازن طریقہ ہے جو مطلوبہ زمینی خاصیت (یہاں میر اذرات کی مقدار) کا نقشہ بنانے کے لیے استعمال ہوتا ہے جب کھیت میں سے کافی تعداد میں زمینی نمونے لیے گئے ہوں (مثلاً ۵۰ سے زیادہ)۔ میر اذرات کی پیائش کی درستگی کو بڑھایا جاسکتا ہے اگر مختلف حساسوں کے متغیرات جو میر اذرات سے اچھا باہمی ارتباط اور مکانی ساخت رکھتے ہوں، کو استعمال کیا جائے۔ اس تجربے میں ہم نے چار متغیرات تھوریم (گیمارے طیف پیما سے)، ای ایم۔۳۸ کی افقی سمت میں برقی ایصالیت اور مرئی اور قصیر زیر سرخ طیف پیما کے طول موج ۳۸۸ اور طول موج ۱۱۸۸ استعمال کیے۔ یہ متغیرات کھیت کے مختلف حصوں سے مختلف طریقوں سے لیے گئے۔ مثال کے طور پر تھوریم کی پیائش پٹیاں (ٹرانزیکٹ) منتخب کر کے آن لائن کی گئی جبکہ دوسرے متغیرات کو مخصوص جگہوں پر صرف میر اذرات کی پیائش والی جگہوں (یعنی ۷۲ جگہوں سے) سے ناپا گیا۔ ہم نے یونیویریٹ ارضی شماریات جیسا کہ عام کریگنگ کو میر اذرات کے نقشے بنانے کے لیے استعمال کیا اور ملٹی ویریٹ ارضی شماریات جیسا کہ یونیورسل کریگنگ (جب تھوریم کو میر اذرات سے نسبت دی گئی)، کوکریگنگ (جب برقی موصلیت اور طول موج کو میر اذرات سے نسبت دی گئی) اور یونیورسل کوکریگنگ (جب تمام متغیرات کو میر اذرات سے نسبت دی گئی) کو استعمال کیا۔ کراس ویلیڈیشن کے نتائج یہ ظاہر کرتے ہیں کہ ارضی شماریات (یونیورسل کوکریگنگ) نے تمام حساسوں کے متغیرات کو استعمال کر کے میر اذرات کی پیشگوئی کی کوالٹی کو بہت زیادہ بہتر بنایا (R^2 کی قیمت 0.65 سے بڑھ کر 0.87 ہو گئی)۔ اسی طرح غلطی کا امکان 0.80 (عام کریگنگ) سے کم ہو کر 0.47 (یونیورسل کوکریگنگ) ہو گیا جو کہ تقریباً نصف ہے۔ ارضی شماریات اس لیے بھی اہم ہے کہ تجزیے کے لیے لیے گئے نمونے ہمیشہ کافی نہیں ہوتے جو کہ اس تبدیلی کو محسوس کر سکیں جیسے زمینی خواص کھیت میں تبدیل ہوتے ہیں۔ اس معاملے میں اگر زمینی خواص اتصالی حساسوں کے ساتھ اچھا ارتباط رکھیں تو زیادہ گنجائی سے ناپے گئے حساسوں کے متغیرات زمینی خواص میں تبدیلی کو زیادہ اچھے طریقے سے معلوم کر سکتے ہیں جو زمینی نمونوں کی

تعداد کو مزید کم کرتے ہیں۔ اس مطالعہ سے یہ نتیجہ اخذ کیا جاتا ہے کہ ارضی شماریات سے اتصالی حساسوں کے مواد کا اختلاط میرا ذرات کی پیشگوئی کی کوالٹی کو واضح طور پر بہتر بناتی ہے اگرچہ اس مطالعہ میں یہ بہتری زیادہ نہیں ہے۔ اسکی وجہ یہ ہے کہ میرا ذرات اور دوسرے متغیرات کے سطحی ساخت میں کچھ فرق ہے۔

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The work done in this thesis brings precision agriculture a step forward towards its implementation. In this thesis, the potentials of different proximal soil sensors were explored and sensor data fusion was performed in the framework of precision agriculture. I hope this work will contribute to the scientific knowledge of precision agriculture.

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togethers on our cultural events. I wish you success and good luck with your current and future endeavours.

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Curriculum vitae

Hafiz Sultan Mahmood was born on July 5, 1978 at Jahangir Khurd, Faisalabad, Punjab, Pakistan. He passed his Secondary School Certificate Examination (Matriculation) in 1994 from Government High School, Jahangir Khurd, Faisalabad. Then he got admission in Pre-Engineering subject in Government College of Science, Faisalabad and passed his Higher Secondary School Certificate Examination (Intermediate) in 1996. After completing college education, he got admission in University of Agriculture, Faisalabad, where he got a four year BSc Agricultural Engineering degree in 2001. His final year's thesis report was about studying the feasibility of energy production from the press mud (bagasse or waste) of sugar mills. After completing the Bachelor degree, he started his Master in Agricultural Engineering in the same University and completed his MSc (Hons.) Agricultural Engineering degree in 2004. During his Master degree, he worked on a project funded by Ministry of Science and Technology, Government of Pakistan. His Master thesis was focussed on designing and developing an environmentally effective boom sprayer for cotton crop. While finalising his Master degree in 2004, he got a job as an Assistant Agricultural Engineer in Pakistan Agricultural Research Council (PARC), Islamabad, Pakistan. Since then, he has been serving for PARC. In 2007, he won an Overseas Scholarship from Higher Education Commission (HEC), Pakistan for obtaining his PhD. He obtained study leave from PARC and started his PhD in Wageningen University, The Netherlands, in January 2008. His PhD research was focussed on the use of proximal soil sensors to estimate several soil properties and to explore possibilities of data fusion from multiple soil sensors to enhance the effectiveness of available soil sensors.

List of publications

1. **Mahmood, H.S.**, M. Iqbal, T. Hamid and K.A. Hussain. 2004. Efficacy of environmentally effective university boom sprayer for bollworm mortality. Pak. J. Agri. Sci., Vol. 41 (1-2).

2. **Mahmood, H.S.**, M. Iqbal, K.A. Hussain and T. Hamid. 2004. Improved surface coverage with environmentally effective university boom sprayer. Pak. J. Agri. Sci., Vol. 41 (1-2).

3. Iqbal, M., **H.S. Mahmood** and M. Younis. 2005. Development of a Drop-pipe Type University Boom Sprayer. J. Eng. & appl. Sci. Vol. 24 No. 2.

4. **Mahmood, H.S.**, Hoogmoed, W.B. and Van Henten, E.J. 2009. Combined sensor system for mapping soil properties. In: E.J. Van Henten, D. Goense and J.F.M. Huijsmans (Editors), Precision agriculture - Proceedings of the European Conference on Precision Agriculture. Wageningen Academic Publishers, Wageningen, The Netherlands, pp. 423-430.

5. **Mahmood, H.S.**, Hoogmoed, W.B. and Van Henten, E.J. 2011. Estimating soil properties with a proximal gamma-ray spectrometer using windows and full-spectrum analysis methods. In: V.I. Adamchuk and R.A. Viscarra Rossel (Editors), Proceedings of the Second Global Workshop on Proximal Soil Sensing, Montreal, Quebec, Canada, pp. 132-135.

6. Kuang, B., **Mahmood, H.S.**, Quraishi, M.Z., Hoogmoed, W.B., Mouazen, A.M. and Van Henten, E.J. 2012. Sensing soil properties in the laboratory, in situ and on-line - a review. Advances in agronomy, 114(1): 155-223.

7. **Mahmood, H.S.**, Hoogmoed, W.B. and van Henten, E.J. 2012. Sensor data fusion to predict multiple soil properties. Precision Agriculture, 13(6): 628-645.

8. **Mahmood, H.S.**, Bartholomeus, H.M., Hoogmoed, W.B. and van Henten, E.J. Evaluation and implementation of Vis-NIR spectroscopy models to determine workability. Submitted to Soil & Tillage Research Journal.

9. **Mahmood, H.S.**, Heuvelink, G.B.M., Hoogmoed, W.B. and van Henten, E.J. Mapping clay content using geostatistical sensor data fusion. Submitted to Vadose Zone Journal.

10. **Mahmood, H.S.**, Hoogmoed, W.B. and van Henten, E.J. Proximal gamma-ray spectroscopy to predict soil properties using windows and full-spectrum analysis methods. Submitted to Sensors Journal.

PE & RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC), which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of literature (6 ECTS)

- Wrote a review article entitled, "Sensing soil properties in the laboratory, in-situ and on-line – A review" and was published (together with inputs from UK colleagues) in Advances in Agronomy Journal
- This work was presented in a meeting of the SPAM discussion group

Writing of project proposal (4.5 ECTS)

- Combined sensor system for soil property sensing (2008)

Post-graduate courses (4.5 ECTS)

- Introduction to R for statistical analysis; PE&RC (2008)
- Module linear models; PE&RC (2009)
- Multivariate analysis; PE&RC (2009)
- Geostatistics; PE&RC (2010)

Laboratory training and working visits (0.9 ECTS)

- Visited UK to have a meeting with an active group in soil sensing; Cranfield University, UK (2009)
- Visited a private company to learn about a gamma-ray spectrometer; Soil Company, Groningen, the Netherlands (2009)
- Visited other institutes to get more insight on more soil sensing methods; BLGG and NMI (Nutrient Management Institute), Oosterbeek, the Netherlands (2009)

Deficiency, refresher and brush-up courses (7.5 ECTS)

- Remote sensing (2008)
- Basic statistics (2009)

Competence strengthening / skills courses (1.8 ECTS)

- Information literacy including introduction EndNote; WGS (2008)
- Techniques for writing and presenting a scientific paper; WGS (2011)

PE&RC annual meetings, seminars and the PE&RC weekend (2.1 ECTS)

- PE&RC Weekend (2008)
- PE&RC Day (2008): accelerate scientific progress – expect the unexpected (2008)
- Participated in a seminar on "Remote Sensing of Environment" (2009)
- PE&RC Day: intelligent communication – on the origin of communication (2009)
- PE&RC Day: innovation for sustainability – what are the neighbours doing? (2011)

Discussion groups / local seminars / other scientific meetings (5.4 ECTS)

- SPAM Discussion group of PE&RC (2008-2011)
- Presentation at expert meeting of Basis project and open day at Lelystad (2010)
- Presentation at expert meeting of Basis project at Lelystad (2010)
- R User meeting (2011)
- Presentation at expert meeting of Basis project and open day at Lelystad (2011)

International symposia, workshops and conferences (4.1 ECTS)

- Delivered an oral presentation on the topic: "Combined sensor system for mapping soil properties"; Joint International Agricultural Conference (JIAC), Wageningen (2009)
- Delivered an oral presentation on the topic: "Estimating soil properties with a proximal gamma-ray spectrometer using windows and full-spectrum analysis methods"; The Second Global Workshop on Proximal Soil Sensing, Montreal, Canada (2011)

Supervision of 2 MSc students; 10 days (3.0 ECTS)

- Field evaluation of a WET sensor
- Root-zone ECa measurement with an EM38 and investigation of spatial interpolation techniques

Colophon

Design and layout of thesis:	Hafiz Sultan Mahmood
Cover design of thesis:	Syed Jalal ud Din Bukhari
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