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Heterogeneity of soil properties at the field-scale and spatial patterns of soil-borne pests and weeds

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Abstract

Soil heterogeneity at the field-scale not only affects crop growth and yield, but also spatial patterns of soil-borne pests and weeds. Therefore, site-specific management in due consideration of soil variability is required within the scope of precision crop protection. The focus of this study was the use of minimal- and non-invasive sensor technologies at the field-scale to improve (i) the assessment of soil organic carbon (SOC), (ii) management strategies for the beet cyst nematode *Heterodera schachtii* and (iii) the appreciation for complex interrelations of soil properties and weeds.

A detailed knowledge on high-resolution SOC heterogeneity in agricultural soils is required, because SOC affects other soil properties such as aggregate stability or soil respiration. The small-scale spatial variability of SOC was determined using imaging spectroscopy in the visible and near-infrared region on long-term uniformly cultivated test fields with varying soil surface conditions (roughness, vegetation). Soil reflectance was recorded by the aircraft-mounted hyperspectral sensor HyMap (450 – 2500 nm). Site-specific characteristics affected the calibration models; highest prediction accuracy was performed over a bare, fine soil (R^2 = 0.80). A generated pixel-wise map (8 × 8 m) on the basis of hyperspectral data visualise the SOC heterogeneity more realistic than an interpolated map based on conventional soil sampling.

Soil texture is often referred to be the dominant soil property affecting the population density of the beet cyst nematode *H. schachtii*. The apparent electrical conductivity (EC_a), which is known to be strongly related to soil texture and porosity, was measured with the non-invasive EM38 sensor. On fields heterogeneous in texture and porosity, moderate (R^2 = 0.47) and strong (R^2 = 0.74) correlations were observed between EC_a and nematode population density. EC_a values and soil taxation maps reveal that *H. schachtii* prefers deep soils with medium to light texture, a high proportion of wide pores and non-stagnic water conditions. Management maps on the basis of EC_a and soil taxation maps indicate areas with different soil-related living conditions for *H. schachtii*.

The spatial distribution and density of four weed species was observed within a long-term survey over nine years on an arable field and related to soil properties. The dominance of the weed species varied between the years, but the spatial patterns remained stable during the whole study period. Soil properties were analysed conventionally in the laboratory and via mid-infrared spectroscopy-partial least squares regression (MIRS-PLSR) or EM38 measurements. Multivariate statistics were used to describe the effect of soil properties, indicating that soil texture, available water capacity and SOC explained 28.2% of the weed species variability. The spatial distribution of soil properties can be used to create maps for site-specific weed management.

The study provide evidence that minimal- and non-invasive sensor technologies such as MIRS-PLSR, airborne hyperspectral imaging or EM38 measurements are practical methods to detect soil heterogeneity at the field-scale. SOC and soil texture, both important parameters for the occurrence of soil-borne pests and weeds, can be characterised with high spatial resolution. Management maps on the basis of soil properties permit several benefits for precision crop protection, such as improved site-specific management strategies of pests and weeds.

Kurzfassung

Die räumlich heterogene Verteilung von Bodeneigenschaften auf der Feldskala beeinflusst nicht nur das Wachstum und den Ertrag von Feldfrüchten, sondern auch das nesterweise Auftreten von bodenbürtigen Krankheiten und Unkräutern. Die Bodenheterogenität auf der Feldskala ist daher ein bedeutender Parameter für teilschlagspezifische Bewirtschaftungsmaßnahmen, wie sie im Präzisionspflanzenschutz gefordert sind. Im Rahmen dieser Arbeit wurden minimal- und nicht-invasive Sensoren eingesetzt, um (i) die Erfassung des organischen Kohlenstoffgehaltes (C_{org}) im Boden, (ii) Bewirtschaftungsstrategien bei Auftreten des Rübenzystennematoden *Heterodera schachtii* sowie (iii) das Verständnis von komplexen Beziehungen zwischen Bodeneigenschaften und Unkräutern zu verbessern und zu automatisieren.

Die hoch aufgelöste, detaillierte Erfassung des C_{org}-Gehaltes in landwirtschaftlich genutzten Böden ist von großer Bedeutung, da der C_{org}-Gehalt des Bodens andere Bodenparameter wie Aggregatstabilität oder Bodenatmung beeinflusst. Die kleinräumige Variabilität von C_{org} wurde auf langjährig einheitlich bewirtschafteten Ackerschlägen mit unterschiedlicher Oberflächenbeschaffenheit (Rauhigkeit, Vegetation) mittels bildgebender spektroskopischer Verfahren im sichtbaren und nahen Infrarotbereich gemessen. Dabei wurde die Reflektion des Bodens mit einem flugzeuggetragenen Hyperspektralsensor (HyMap, 450 – 2500 nm) erfasst. Die Vorhersagegenauigkeit von C_{org} variierte je nach Oberflächenbeschaffenheit und war bei unbewachsenem, feinkörnigem Boden am höchsten (R^2 = 0,80). Die Verteilung des C_{org}-Gehaltes konnte mit einer pixelweisen Karte (8 × 8 m), basierend auf hyperspektralen Daten, mit einer höheren Genauigkeit dargestellt werden als mittels einer interpolierten Karte auf der Basis einer konventionellen Bodenprobenahme.

Die Populationsdichte des Rübenzystennematoden *H. schachtii* wird häufig mit der Bodentextur in Verbindung gebracht. Der nicht-invasive Sensor EM38 wurde zur Messung der scheinbaren elektrischen Leitfähigkeit (EC_a) eingesetzt, die wiederum von der Bodentextur und der Porosität des Bodens beeinflusst wird. Auf texturell heterogenen Flächen wurden moderate (R^2 = 0,47) bis enge (R^2 = 0,74) Beziehungen zwischen der EC_a und der Populationsdichte des Nematoden beobachtet. Die Verteilung der EC_a sowie Bodenschätzungskarten verdeutlichen, dass *H. schachtii* tiefgründige Böden von sandig-schluffiger Textur mit einem hohen Anteil an Grobporen ohne wasserstauende Bedingungen bevorzugt. Bewirtschaftungskarten auf Grundlage von EC_a- und Bodenschätzungskarten kennzeichnen Teilflächen mit variablen bodenbezogenen Lebensbedingungen für *H. schachtii*.

Die räumliche Verteilung und Dichte von vier Unkrautarten wurde im Rahmen einer Langzeitstudie von neun Jahren auf einer Ackerfläche erfasst und mit der vorliegenden Bodenheterogenität verglichen. Während der gesamten Studie konnte eine starke Ortsgebundenheit der Unkräuter beobachtet werden, auch wenn der Deckungsgrad zwischen den Jahren variierte. Die Bodeneigenschaften wurden entweder konventionell im Labor analysiert und / oder anhand mittlerer Infrarot-Spektroskopie (MIRS) und EM38-Messungen erfasst. Mittels multivariater Statistik wurde der Einfluss des Bodens auf die Unkrautvariabilität bestimmt. Diese wurde zu 28,2% durch die Bodentextur, die nutzbare Feldkapazität und den Gehalt an C_{org} beeinflusst. Die heterogene Verteilung von Bodeneigenschaften kann genutzt werden, um Karten für eine teilflächenspezifische Unkrautbewirtschaftung zu erstellen.

Die Ergebnisse dieser Arbeit zeigen, dass minimal- und nicht-invasive Sensoren zur Erfassung der Bodenheterogenität (C_{org}, Bodentextur) auf der Feldskala geeignet sind. Die Untersuchungen und dargestellten Karten basierend auf der Bodenheterogenität zur räumlich heterogenen Verteilung von Nematoden und Unkräutern belegen, dass auf dieser Grundlage teilschlagspezifische Bewirtschaftungsmaßnahmen im Rahmen des Präzisionspflanzenschutzes möglich sind.

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AICc	Corrected Akaike Information Criterion
AWC	Available Water Capacity
BCN	Beet Cyst Nematode
C_t	Total Carbon
DCA	Detrended Correspondance Analysis
EC	Electrical Conductivity
EC_a	Apparent Electrical Conductivity
EF	Modelling Efficancy
GWR	Geographically Weighted Regression
IDW	Inverse Distance Weighting
IR	Infrared Reflectance
MIR	Mid-Infrared
MIRS	Mid-Infrared Spectroscopy
NIR	Near Infrared
NIRS	Near Infrared Spectroscopy
N_t	Total Nitrogen
PLSR	Partial Least Squares Regression
POM	Particulate Organic Matter
RDA	Redundancy Analysis
RMSECV	Root Mean Square Error of Cross Validation
RMSEP	Root Mean Square Error of Prediciton
RPD	Ratio of Performance to Deviation
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SWIR	Shortwave Infrared
VIS	Visible Reflection

Contents

I

Introduction

1 RATIONALE

Today´s agricultural production faces major challenges: the rapid growth of the human world population, accompanied consumption of food and thus an increasing use of agricultural land and resources as well as the rising costs of agricultural production (FAO, 2001; Brown, 2006). It is almost impossible to solve these challenges with conventional farming practices. One possible approach is precision farming (Stafford, 2000; Gebbers and Adamchuk, 2010). Precision farming, or precision agriculture, aims to match both agricultural input and practices to the variation of soils, crops, pests and weeds within a field, instead of the uniform and suboptimal management of an entire field. Thereby, precision agriculture implements the accurate, rapid and economical acquisition of the spatial and temporal variability with a high spatial resolution (Viscarra Rossel and McBratney, 1998).

Precision crop protection can be considered as a significant part of precision agriculture. One main objective of precision crop protection is site-specific management of pests and weeds to achieve ecological and economic benefits from the saving of pesticides (Timmermann et al., 2003; Maxwell and Luschei, 2005; Patzold et al., 2008). Thereby, crop protection due to pesticide applications can become more precise in crop production, leading to reduced costs and less environmental burdens (Stafford, 2000). As reviewed by Stafford (2000), the first real application of precision agriculture was a site-specific fertilisation system implemented in 1988. Atkinson and McKinlay (1997) stated that it is important to find alternative technologies to control plant diseases and weeds without impairing the environment, but with increasing yield and product quality. Therefore, precision agriculture, including precision crop protection, was in the focus of many studies concerning new techniques for herbicide application (Gerhards and Christensen, 2003), digital soil mapping (Triantafilis et al., 2009) or detection of diseases (Rumpf et al., 2010) at the field-scale.

An important aspect within precision crop protection is the spatial heterogeneity of soil properties at the field-scale. The spatial variability of soil properties affects crop growth and thus yield (Stafford, 2000), the occurrence of soil-borne pests and weeds (Patzold et al., 2008), plant parasitic diseases (Dordas, 2008) as well as the leaching and efficacy of pesticides in soil (Wauchope et al., 2002; Mertens, 2008). The acquisition and mapping of soil heterogeneity can help to develop and to improve site-specific management strategies within precision farming practices (Gebbers and Adamchuk, 2010).

Within the scope of precision farming, new technologies are needed to reduce costs and time for soil sampling and analysis, including the simultaneous improvement of the accuracy of the results (Viscarra Rossel and McBratney, 1998). Thus, real-time sensing and online applications with high spatial resolution are required (Gebbers and Adamchuk, 2010). In the past decade, several sensors for the determination of soil chemical and physical properties have been developed and tested. Soil chemical properties, such as soil organic carbon (SOC), can be detected with spectral sensors operating in the visible (VIS), near-infrared (NIR) and mid-infrared (MIR) region (Viscarra Rossel et al., 2006; Bornemann et al., 2008; Patzold et al., 2008; Stevens et al., 2010). Further soil properties including physical parameters are measurable by non-invasive sensors such as the EM38 (Geonics, Canada) or the Veris 3100 (Veris Technologies, USA). These sensors can be directly used in the field to measure the (apparent) electrical conductivity (EC_a) as an indicator for soil salinity, clay content and soil moisture (Sudduth et al., 2005; Mertens et al., 2008). Based on results from sensor technologies, highly resolved management maps can be created to support agronomists and farmers to manage land in a sustainable, environment-friendly and site-specific way (Oliver and Webster, 1991). The use of sensor technologies to assess chemical and physical soil properties such as SOC and soil texture at the field-scale, their effects on the patchy occurrence of pests and weeds and the creation of related site-specific management maps were the aims of this PhD-thesis.

2 STATE OF THE ART

2.1 Heterogeneity of soil properties at the field-scale

Arable fields are often characterised by considerable spatial soil heterogeneity, even though land management for a given field has been uniform over recent decades. The spatial and temporal variability of soils depends on the main factors parent material, climate, topography, organisms (including vegetation) and time (Jenny, 1941). Consequently, physical, chemical and biological soil characteristics are spatiotemporal heterogeneously distributed within arable fields; variation in soil properties occur in both horizontal and vertical directions (Viscarra Rossel and McBratney, 1998; Patzold et al., 2008). Furthermore, agricultural practices such as cultivation, liming or fertilisation affect the variability of soil properties like plant available nutrients, which, in turn, affect crop yield (Viscarra Rossel and McBratney, 1998).

Human-induced factors like soil tillage as well as geological reasons like land surface relief and topography affect soil heterogeneity. Soil erosion and deposition of SOC and plant available nutrients are known to be strongly correlated and further affected by the type of soil tillage (De Gryze et al., 2008). Stevens et al. (2010) related SOC variability at the field-scale to differences in land-management or land use history, such as the former use of land for grassland instead of arable land. Variation in soil texture is mainly affected by soil forming processes. The different horizons of a soil depend on the parent material and can be mixed due to erosion, cryoturbation or solifluction (Mertens et al., 2008).

Soil texture, SOC, nutrients and pH are reported to be highly relevant to precision farming, because their spatial distribution directly or indirectly affects crop growth and thus crop yields (Viscarra Rossel and McBratney, 1998; Dordas, 2008; Mertens et al., 2008). Due to regular fertilisation and liming, leading to a high nutrient supply and an equalised soil pH, the effect of nutrients and soil pH can be regarded as negligible in many agricultural fields. In contrast, soil texture and SOC are particularly important soil properties affecting other soil parameters such as soil porosity, aggregate stability or soil respiration.

The spatial variation of soil properties within fields offers various conditions for a diverse development of crops as well as for many soil-borne pests and weeds (Patzold et al., 2008). Also sorption and desorption processes of pesticides are affected by the amount and quality of SOC, texture, pH and soil moisture content (Wauchope et al., 2002; Mertens, 2008). Thus, a detailed knowledge about the spatial variability of soil properties is essential for implementing precision crop protection into the concept of precision farming (Patzold et al., 2008).

The spatial distribution of SOC and soil texture within a field affects various crop stand parameters such as crop nutrient status or crop yield and the related amount and distribution of fertiliser needed. In addition, SOC and soil texture are closely related to soil quality, as they perform as indicators of soil erosion and degradation (Selige et al., 2006; De Gryze et al., 2008). Depending on land-use and management, agricultural soils can be a major source or sink for carbon (Sleutel et al., 2007; Lal, 2010). In consequence, high-resolution SOC determination is of high interest beyond the needs of precision farming. It is also required for a contemporary environmental monitoring. Due to their diverse significance, SOC and soil texture heterogeneity at the field-scale were the main soil properties focused in this study.

2.2 High-resolution qualitative and quantitative assessment of soil organic carbon and soil texture

A high sampling density is required within precision agriculture to improve accuracy for site-specific management decisions and for the creation of management maps, also with respect to geostatistical needs (Viscarra Rossel and McBratney, 1998; Chang et al., 2001; Stevens et al., 2006). However, manual soil sampling and laboratory analyses are laborious and expensive (Stafford, 2000). The use of sensor technologies and comprehensive sampling strategies needs less time effort and less manpower than conventional techniques. Thus, innovative sensor technologies for the determination of soil heterogeneity are required and already partially used (Milton et al., 2009; Adamchuk et al., 2010). For the detection of SOC and soil texture, the related techniques are introduced in the following sections 2.2.1 and 2.2.2, respectively. Additionally, sampling strategies such as nested sampling can improve sampling efforts and optimise sampling strategies with economic benefits (Oliver and Webster, 1986; Viscarra Rossel and McBratney, 1998). They are the basis of advanced geostatistical procedures (see section 2.2.3).

2.2.1 Determination of soil organic carbon via spectral sensors

Various soil properties can be quantitatively measured with spectral sensors due to their specific reflectance properties (Baumgardner et al., 1985). Soil reflectance in the wavelength range between 400 and 25,000 nm derives from the spectral behaviour of the heterogeneous combination of organic matter, minerals, water and other chromophores (Udelhoven et al., 2003). A chromophore is part of a molecule that causes it to be coloured and that significantly affects the shape and nature of a soil spectrum (Hill et al., 2010). Reflectance spectra of soil can be transformed to quantitative estimates of soil constituents using infrared (IR) spectroscopy, as reviewed by Ben-Dor et al. (2009).

Spectroscopy in the VIS, NIR and MIR region is an efficient and rapid technology which can provide soil data at a high spatial and temporal resolution (Viscarra Rossel et al., 2006; Gomez et al., 2008; Stevens et al., 2010). VIS, NIR and MIR techniques are reported to be highly sensitive, namely to the organic components of a soil. Spectral signatures related to various components of soil organic matter (SOM) generally occur in the MIR range (2500 – 25,000 nm), but their overtones can also be found in the VIS/NIR (400 – 1200 nm) and the shortwave-infrared (SWIR; 1200 – 2500 nm) ranges (Shepherd and Walsh, 2002). Several studies reveal that on average MIR outperforms VIS/NIR, because MIR spectra consist of more defined peaks and thus are often described as performing better in estimating the SOC content (Chang et al., 2001; Stevens et al., 2006; Viscarra Rossel et al., 2006; Patzold et al., 2008; Ladoni et al., 2010; Reeves, 2010). Due to its increasing use and wide acceptance, MIR spectroscopy (MIRS) may be considered as a reference method, even if it's not yet an established laboratory standard. However, due to the fact that no transportable MIR sensor exist, MIRS is to be used preferentially under laboratory conditions, while NIR spectroscopy (NIRS) can be easily applied in the field as portable or as airborne sensors (Christy, 2008).

NIRS has been used for several years for the assessment of SOC (Dalal and Henry, 1986; Henderson et al., 1992). Ladoni et al. (2010) reviewed the satisfying ability to predict SOC via NIRS under laboratory conditions. However, the choice of spectroscopic techniques used in field studies depends mainly on the accuracy of prediction, the cost of the technology and the amount of sample preparation required (Viscarra Rossel et al., 2006). To enhance the efficacy of spectroscopic techniques for soil mapping and monitoring, airborne sensor applications are becoming more popular, though they remain in the testing phase (Selige et al., 2006; Patzold et al., 2008; Stevens et al., 2008, 2010). According to DeTar et al. (2008), soil properties can be accurately detected using airborne hyperspectral imaging due to its high spatial resolution and supplying a complete spectrum of data for every pixel location.

Multivariate calibrations, such as partial least squares regression (PLSR), allow for a quantitative determination of several soil characteristics from spectral signatures (VIS, NIR, SWIR and MIR) and are a common tool to derive soil properties from spectral data (Selige et al., 2006; Viscarra Rossel et al., 2006; Stevens et al., 2010). However, airborne hyperspectral imaging still has several limitations, as reviewed by Ben-Dor et al. (2009) and Cécillon et al. (2009). These limitations can be atmospheric absorptions or sensor-based characteristics such as a low signal-to-noise ratio and a limiting spatial resolution, or can occur due to spatial and temporal soil surface conditions, such as variable moisture content, soil surface roughness, or green manure or crop residue covers. In consequence, local calibration outperforms regional calibration (Stevens et al., 2010). The airborne HyMap sensor has shown itself to be an appropriate tool to monitor SOC at a regional scale (Selige et al., 2006).

2.2.2 Determination of soil heterogeneity via electromagnetic induction

The non-invasive sensor EM38 uses electromagnetic induction for mapping the EC_a. The principle of electromagnetic induction is as follows: A transmitter coil at one end of the sensor induces an electromagnetic field in the soil, which is directly proportional to the electrical conductivity (EC). Each current loop generates a secondary electromagnetic field which is intercepted by a receiver coil at the other end of the sensor and summed up to the EC_a. The EC_a measures conductance through the soil solution as well as through solid soil particles and exchangeable cations at soil-liquid interfaces of clay minerals (Corwin and Lesch, 2003).

Thus, several soil properties, predominantly soil salinity, clay content and actual soil moisture are directly or indirectly correlated with the EC_a (Friedman, 2005; Sudduth et al., 2005). Soil salinity can be regarded as negligible in Western Europe, where soils are usually free of soluble salts and the salt concentration of the soil solution is < 2 cmol L^{-1} (Rhoades et al., 1989). Hence, at comparable soil moisture conditions, the EC_a can serve as an alternative indicator for soil texture. Mertens et al. (2008) suggested to perform repeated measurements several times at days with almost constant temperatures during the winter, when soil moisture content is close to field capacity. Thereby, disturbances by variable water content and soil temperature should be minimised and, in turn, achieved mostly stable patterns of the clay content.

The EC_a signal is an integral over the soil depth up to 1.5 m and thus covers the complete root zone (Domsch and Giebel, 2004). The precision of the results from EM38 measurements can be improved by additional local calibration with ground truth data to compensate the missing depth resolution (Mertens et al., 2008). High numbers of measurement points can easily be recorded. Thus, EC_a maps with a very high spatial resolution can be created. During the last decade, the sensor EM38 has proven to be an useful, efficient and inexpensive mapping technique of soil texture and further soil heterogeneity at the field-scale (Sudduth et al., 2001; Domsch and Giebel, 2004; Mertens et al., 2008).

2.2.3 Geostatistical treatment of ground truth and sensor data

Management maps including within-field spatial variation of different parameters relevant for precision crop protection (e.g. soil properties, disease detection, weed species abundance) are needed by agronomists and farmers to improve site-specific management strategies (Oliver and Webster, 1991; Viscarra Rossel and McBratney, 1998). An area-wide sampling is required for creating maps, expressing spatial patterns of entire fields. The use of geostatistics, including semivariogram analysis is frequently accepted and performed for visualising spatial variation (Kuzyakova and Richter, 2003; Bilgili et al., 2010). Therefore, at least 100 point data are necessary to create a semivariogram and thus to state about the spatial correlation of a parameter (Oliver and Webster, 1991).

Conventional assessment of ground truth data is laborious and expensive and often results in too large or too small sampling densities and thus to large estimation uncertainties (Stafford, 2000; Nutter et al., 2002). E.g., only averaged SOC contents within arable fields are determined in the current agricultural practise (Preger et al., 2006), whereby spatial SOC heterogeneity cannot be detected adequately. Grid sampling is a widespread method to detect the intensity of nematodes or weeds within fields, as reviewed by Webster (2010). However, even a small-scale grid size can miss spatial heterogeneity, if the patchy distribution of a given parameter occurs between the intersection points of the sampling grid. High-resolution sensor data from soil sensors as well as from sensor techniques for the determination of pests and weeds are therefore needed to detect small-scale spatial variability.

The concept of 'digital soil mapping' contains the use of sensor technologies to create soil maps with a high spatial resolution for a further integration of soil properties into precision crop protection (McBratney et al., 2003). Thereby, conventional soil sampling and laboratory analysis are combined with sensor data and geostatistical methods (Behrens and Scholten, 2006). Furthermore, pedotransfer functions should be used to evaluate soil properties on the basis of soil characteristics detected by sensor data (Mertens et al., 2008). Digital soil mapping is a part of many recent studies (Behrens et al., 2010; Grimm and Behrens, 2010; Malone et al., 2011). However, sensor data are not available for the detection of all required parameters within precision crop protection. Thus, the focus of this study was not on digital soil mapping, but on the quantitative detection of spatial soil heterogeneity and related soil-borne pests and weeds.

The spatial distribution of a parameter at various short- and long-range distances can be adequately predicted using the nested sampling design and geostatistics for data analysis instead of conventional or grid sampling (Webster and Boag, 1992; Avendaño et al., 2003). The nested sampling scheme provides a range of intervals to ensure that spatial variation within a given field would be resolved. The original nested sampling design to analyse spatial scale was proposed by Youden and Mehlich (1937). This was a balanced scheme in which the sampling was fully replicated at each level. Oliver and Webster (1986) introduced an unbalanced design for economy, which was adopted in this study. The design economises the sampling strategy to allow more main centres and stages. The basis of the design is that a population can be sampled with a multi-level or nested scheme that enables the variance to be estimated for each level. The total variance is the sum of the contributions from each level in the hierarchy. The theory of nested sampling is described in detail by Oliver and Webster (1986).

Additional variogram analyses using geostatistics can improve sampling strategies and estimation accuracy, because the experimental variogram implicates information about the spatial variation of a parameter which can be displayed with interpolation methods (Oliver and Webster, 1991; Viscarra Rossel and McBratney, 1998). In comparison with conventional grid sampling, small-scale variability (< grid size) can be detected and visualised on maps with a simultaneous decrease of the amount of samples needed.

2.3 Patchy occurrence of pests within arable fields

The spatial variability of soil properties affects the site-specific distribution of pests within arable fields, as reviewed by Patzold et al. (2008). Dordas (2008) further attributed these interactions to the amount of SOC in soils, influencing plant availability of nutrients, plant growth and plant tolerance against diseases. Kiss and Potyondi (2000) observed positive relationships between the nutrient supply of soils and the tolerance of sugar beets against fungal plant pathogens. Beside foliar diseases, especially the patchy occurrence of soil-borne pathogens can be related to soil heterogeneity. E.g., the soil-borne fungus *Rhizoctonia solani*, causing *Rhizoctonia* crown and root rot at sugar beets could be associated with the heterogeneously distributed amount and quality of SOC within arable fields (Kühn et al., 2009b).

Furthermore, several studies have shown that population densities of soil nematodes are related to environmental conditions, in particular to the variation in soil properties. Soil texture is often considered to be the main soil property influencing the population densities of cyst nematodes (e.g. Cooke, 1984; Nombela et al., 1994; Wyse-Pester et al., 2002). Soil texture and the related properties soil structure and soil moisture vary spatially within fields (see section 2.1) and have a considerable effect on nematode population dynamics (Hassink et al., 1993; Workneh et al., 1999; Avendaño et al., 2004). Nombela et al. (1994) observed within large districts that various nematode species favour different textural zones. Avendaño et al. (2004) found higher population densities of the soybean cyst nematode *Heterodera glycines* at sandy sites than at adjacent loamy or clayey sites within agricultural fields.

SOC content and soil texture are reported to affect the occurrence of soil-borne pests. Furthermore, SOC and soil texture are strongly interrelated and further affect other soil properties such as aggregate stability or nutrient supply, indicating the complex interaction within soils. Therefore, one focus of this study was on relationships between soil properties and the occurrence of the beet cyst nematode (BCN), *Heterodera schachtii* (Schmidt), within agricultural fields. *H. schachtii* is a plant parasitic sedentary endoparasite causing severe damage to sugar beet with yield losses up to 50% and is considered one of the most significant pests in sugar beet production in Europe and worldwide (Schlang, 1991; Müller, 1999).

2.3.1 Population dynamics of *Heterodera schachtii* as affected by soil properties

The natural spread of cyst nematodes, and thus the inter- and intra-field distribution, is limited due to their restricted mobility (Freckman and Caswell, 1985). Therefore, the spatial distribution of symptoms caused by *H. schachtii* can appear to be nested within sugar beet fields (Petherbridge and Jones, 1944; Cooke, 1987). Second stage juveniles of *H. schachtii* (J2) penetrate the lateral root tips of sugar beet plants. After penetration, J2 initiate the formation of giant cells (syncytia) in the vascular system. As a consequence, the nutrient and water uptake by the infested root is disrupted, resulting in reduced growth and a decrease in yield of the affected plant. Branched tap roots are developed due to compensatory secondary root growth (Cooke, 1987). Infested plants often wilt late in the growing season, especially if exposed to stress from heat and water conditions (Schmitz et al., 2006; Hillnhütter et al., 2011a).

Soil texture, moisture and temperature have been identified as the most important properties that affect plant parasitic nematodes (Wallace, 1959, 1968; Cooke and

Thomason, 1979; Caswell et al., 1986; Schmidt et al., 1993; Avendaño et al., 2004). The effect of soil texture on nematode populations can be explained by various simple, as well as by more complex, effects. Soil texture has an indirect effect on the living conditions of nematodes, because it affects the diameter and distribution of soil pores, and – in a more complex way – SOC content and soil aggregation, both in determining the size and the accessibility of the nematodes' living space. Raski (1950) found that the plant penetrating mobile J2 stage of *H. schachtii* reached 22 µm in diameter. Consequently, soil pores with a diameter > 22 µm are necessary for the development of BCN. Such pore sizes refer to wide pores and occur mainly in soils dominated by sand (coarse silt and fine sand fraction: 20 – 200 µm). In support of this, Wallace (1968) found the fastest movement of *H. schachtii* in soil with particle sizes of 150 – 250 µm in diameter. Soil with a large fine sand content frequently has soil pores with larger diameters, leading to favourable environmental conditions for BCN development and movement. Therefore, the population density of *H. schachtii* is expected to be highest in this type of soils.

The nematodes' development is not based solely on the geometric properties of the living space, but also on actual environmental conditions, i.e. presence and amount of pore water. Thus, soil water dynamics have to be considered as well. Nematodes need adsorbed water on soil particles for their survival and mobility (Wallace, 1968). According to Wallace (1956, 1959, 1968), the activity and hatching of *H. schachtii* is greatest at field capacity, i.e. when fine (< 0.2 µm), medium (0.2 – 10 µm) and large slow draining (10 – 50 µm) pores are saturated with water. If a soil becomes dry, the lack of water becomes the limiting factor for the hatching, movement and overall persistence of the nematodes (Wallace, 1959; Decker, 1969).

Soil temperature also affects the nematode population dynamics. Many temperature studies of the population dynamics of *H. schachtii* were done under laboratory or greenhouse conditions. They all indicated a clear direct temperature effect, i.e. the higher was the soil temperature the greater was the nematode population activity (Santo and Bolander, 1979; Griffin, 1981b, 1988). However, soil temperatures above 32°C markedly limit nematode activity (Cooke and Thomason, 1979). After the penetration of roots by J2, soil that warms rapidly increases the reproduction of

H. schachtii. Soil temperature and soil texture are directly linked, because the warming of soil in spring and after periods of rain is more rapid in sandy than in loamy or clayey soil; the latter, however, dry out more slowly. Thus, soil texture affects nematodes in a complex way.

Furthermore, soil texture and also SOC content affect the development of the host plant through the supply of nutrients and water. Optimal growth conditions for host plants may lead to a large root biomass, which provide more feeding sites and thus optimal population growth conditions for the nematodes (Avendaño et al., 2003; Evans et al., 2003). On the contrary, circumstances such as water logging or drought stress in shallow or dense soils reduce the development of the host plant, and are also disadvantageous to the development of BCN.

2.4 Patchy occurrence of weeds within arable fields

Beside foliar and soil-borne diseases, weeds are another factor affecting yields of field crops. Weeds cause the most important damages to crops at arable fields across the world with yield losses of 10 to 80% (Cousens and Mortimer, 1995; Oerke and Dehne, 2004). Weed control is demanding, because weed communities react very flexible to new management and control strategies (Sosnoskie et al., 2006). Field crops respond directly to high weed densities by yield reductions, because weeds and field crops compete for growth factors such as light, water and nutrients (Cousens and Mortimer, 1995; Kobusch, 2003; Ritter et al., 2008). Thereby, competition within and between crop and weed species is very complex; individual competitiveness are crop and weed specific and site- and year-dependent (Kobusch, 2003). Field crops with slow juvenile development (e.g. maize, sugar beet) are very susceptible to weed competition at early development stages, whereas field crops with rapid juvenile development (e.g. cereal, rape) are more compressive to weeds (Cousens and Mortimer, 1995; Bräutigam, 1998). Year-dependent weed density can be affected by soil tillage and climatic conditions such as temperature and rainfall (Cousens and Mortimer, 1995; Cardina et al., 2002; Sosnoskie et al., 2006; Long et al., 2011).

Weeds are very adaptable to their environment and usually of general occurrence (Marshall et al., 2003). However, a site-specific species composition and patchiness of weeds with a distinct composition and with different plant densities often occur within arable fields; this is an accepted fact as reviewed by Rew and Cousens (2001) and has been the objective of many studies (e.g. Christensen et al., 2003; Gerhards and Oebel, 2006; Dicke et al., 2007; Ritter et al., 2008; Weis et al., 2008).

The spatial pattern of weeds depends on various environmental and human-induced factors. Minimum and no tillage increase weed density, which, in turn, can be reduced by ploughing (Bàrberi and Lo Cascio, 2001; Cardina et al., 2002). Furthermore, the crop rotation affects weed occurrence (Cardina et al., 2002). Differences in weed species composition were especially found between row crops sown in spring and winter cereals (Andreasen et al., 1991), whereas differences in weed density were observed between summer annual crops and winter annual crops (Hald, 1999). The spatial distribution of weeds can also be affected by herbicide application, whereas weed density can increase if herbicide use is reduced (Squire et al., 2000). Dieleman et al. (1999) stated that the aggregation of weeds may be enhanced by uniform herbicide application, because a greater number of plants may survive in the patch centres and produce new seeds. Dicke et al. (2007) found that the adaption of herbicide active ingredient and dosage to weed species and density does not affect the weed pattern and abundance in a 4-year field crop rotation.

Several authors observed relationships between the patchy distribution of various weed species and spatial soil heterogeneity. SOC, soil texture and nutrient status of the soil can affect weed occurrence (Gaston et al., 2001; Walter et al., 2002; Nordmeyer and Häusler, 2004; Long et al., 2009). Various soil properties are closely interrelated, so that a given parameter such as SOC can be an indicator for other soil conditions, such as water holding capacity. Thus, effects of the soil on weed growth are not monocausal but complex and have to take various interrelations into account (Andreasen et al., 1991).

Weed patches have been observed to be stationary at least for several years (Gerhards and Christensen, 2003). This is an important factor for weed management within the scope of precision crop protection. Therefore, several innovative technologies have been developed to optimise site-specific weed control, as reviewed by Gerhards and

Christensen (2003). Current studies mainly focus on an on-the-go detection of weeds and the use of patch sprayers to reduce herbicide use (Gerhards et al., 2005; Gutjahr et al., 2008). Vehicle-based (Gerhards and Oebel, 2006; Weis et al., 2008), airborne (Gray et al., 2008) or satellite-based (Jacobi et al., 2006) image analysis as well as computerised decision algorithms and modelling (Dunker et al., 2002; Christensen et al., 2003; Ritter et al., 2008) were used for weed detection and species identification. Also geostatistical analyses with varying interpolation techniques are increasingly applied in weed research (Webster, 2010). Kroulik et al. (2008) already combined some of these new approaches and included soil information on the basis of EC_a measurements, resulting in a satisfying prediction accuracy of *Cirsium arvense*. The number and diversity of studies regarding spatial weed distribution highlights the importance of this topic for future precision crop protection strategies.

3 OBJECTIVES

Soil heterogeneity at the field scale is an increasingly recognised fact in crop and soil science. As shown above, spatial soil variability affects many factors of crop growth as well as pest and weed incidence. This study aims at the evaluation of the interrelation between soil heterogeneity and important aspects of crop protection including conditions for crop growth. The aspects examined were SOC, *H. schachtii* and weed distribution.

Relevant soil properties and their spatial distribution within agricultural fields can be detected with innovative non-invasive or minimal-invasive sensor technologies. In this context, a detailed knowledge of the small-scale variability of SOC within individual agricultural fields is an essential requirement for an effective site-specific management within precision crop protection. Furthermore, the patchy occurrence of the plant parasitic cyst nematode *H. schachtii* as well as of weeds has not been studied satisfactorily with respect to underlying soil properties. Management maps were exemplarily developed to improve prospective site-specific management strategies of pests and weeds.

In detail, the following objectives were in the focus of this study:

(i) The prediction of the spatial heterogeneity of SOC at the field-scale was tested using high-resolution airborne hyperspectral imaging (HyMap sensor). Thereby, different soil surface conditions (roughness, vegetation) were investigated. Possibilities and limitations regarding the temporal stability of spatial SOC distribution were evaluated. SOC maps on a pixel-wise basis as required for precision agriculture and for SOC monitoring were generated.

(ii) The development of management maps for *H. schachtii*-infested fields with the use of non-invasive soil sensors was investigated. These maps are based upon soil texture information from EC_a data from the EM38 sensor and additional information from traditional soil taxation maps. The management maps were validated against the observed spatial distribution of *H. schachtii*. Such management maps will enable farmers to use suitable site-specific management strategies and target sampling effectively within fields.

(iii) The relevance of soil properties for weed prediction and detection was evaluated. Modern sensor technologies and multivariate statistical methods are proved to estimate the effect of soil on weed distribution and abundance with higher accuracy than in the past. The occurrence and patchiness of weeds was observed within a long-term survey over nine years on an arable field with respect to spatial soil heterogeneity. Weed management maps on the basis of sensor data and soil maps were created in order to improve the knowledge base for site-specific weed management.

The three different aspects investigated shall contribute to clarify the complex interrelation between soil, crops and pests as well as weeds. The large number of observations due to sensor application potentially opens new perspectives in the field of precision crop protection.

II

Material and Methods

1 MID-INFRARED SPECTROSCOPY

The reflectance properties of the soil were measured in the MIR range and regarded as a laboratory standard. All soil samples were air-dried, sieved (< 2 mm) and further milled. For the implementation of MIRS, ~20 mg aliquots per sample were transferred to microtiter plates and compacted with a plunger to leave a plain and dense surface. Spectra measurements were performed using a Bruker Tensor 27 (Bruker Optik, Ettlingen, Germany) equipped with an automated high throughput device (Bruker HTS-XT), operating with a liquid N_2-cooled mercury-cadmium telluride (MCT) detector. Spectra were recorded from 1250 to 16,700 nm at a resolution of 4 cm^{-1}, thus covering not only the MIR range but also partially including the NIR spectrum. Five measurements, each comprising of 120 scans, were conducted per sample.

2 MULTIVARIATE CALIBRATIONS

A partial least squares regression (PLSR) was used to calibrate the MIRS data with the reference soil data, which were measured with laboratory standards. PLSR for data analyses was performed using OPUS QUANT software (Bruker Optik, Ettlingen, Germany), utilising the PLS 1 algorithm (Martens and Naes, 1996). The removal of certain spectral ranges as well as adequate data treatment of the spectroscopic information are important measures used to enhance the quality of a prediction model (Bornemann et al., 2008). The OPUS QUANT software supplies a routine that automatically tests both measures to ensure the optimum prediction power of the model.

For each sample set a leave-one-out cross validation was conducted, where each sample, comprising of five repetitions, is successively removed once and its value is predicted by the remaining samples. Repetitions that obviously did not fit the prediction model were treated as outliers and removed from the sample sets, upon which cross validation was repeated. The software presents several alternatives which can be used as a calibration model. A robust calibration model is then selected manually to ensure the optimum prediction power of the model. The stability of the prediction models was verified by test-set validation with a ratio of calibration and validation samples of 50%. Thereby the first sample group is applied to derive the model parameters, and the second one is used to validate the applicability of the model, and *vice versa*.

The predictive power of spectroscopic measurements can be described by the coefficient of determination (R^2) between measured and predicted values, the root mean square error of cross validation (RMSECV) and the root mean square error of prediction (RMSEP) for cross validation and test-set validation procedures, respectively. These latter parameters describe the standard errors of the calibration procedures. Furthermore, the ratio of performance to deviation (RPD), the ratio of performance to interquartile distance (RPIQ) and the modelling efficiency (EF) were calculated as dimensionless quality parameters. The RPD represents the quotient of standard deviation of the reference data and standard error of the calibration procedures. According to Chang et al. (2001), calibration models with an RDP > 2 are considered to accurately predict a soil parameter, whereas an RPD < 1.4 indicates no prediction ability. RPD values between 1.4 and 2 belong to an intermediate class. The RPIQ correctly represents the spread of a population and is a useful index for soil samples (Bellon-Maurel et al., 2010). The EF is calculated as the relative deviation of the predicted data compared to the variation in the lab data. It is used to evaluate the model performance and should be as close to 1 as possible (Loague and Green, 1991). Lastly, the bias, which is a measure of the difference between reference and predicted means, was calculated (Bellon-Maurel et al., 2010).

3 MEASUREMENT OF APPARENT ELECTRICAL CONDUCTIVITY

The apparent electrical conductivity (EC_a) was measured with the non-invasive electromagnetic EM38 sensor from the bare soil surface. The vertical-dipole mode, leading to a measurement depth of 1.5 m, was used to cover the complete root zone. The EM38 and a GPS were mounted on a plastic sledge that was pulled over the fields and provided measurements every 2.8 m. The EC_a data were measured on transects separated by about 8 – 10 m. This corresponds to about 430 data points per hectare. Mertens et al. (2008) suggested that EC_a should be recorded on several different days during the winter when temperatures are almost constant and soil moisture content is close to field capacity to minimise any effects from variable water content and soil temperature. Thus, EC_a was measured two to three times during the winter season at each field and averaged.

4 GEOSTATISTICAL DATA ANALYSIS

The geostatistical data processing and the creation of maps were performed using ArcGIS 9.3 (ESRI, Redlands, California, USA). Ordinary kriging was the method of choice to state the spatial prediction of soil properties of the investigated fields. Preceding variogram analyses were performed using VESPER (Minasny et al., 2005) following the standard formula described by Webster and Oliver (2007). Due to partially small sample sets it was not possible to predict a robust variogram and to use kriging at every test site (at least 100 samples are required; Oliver and Webster, 1991). In such cases, soil point data were interpolated by Inverse Distance Weighting (IDW) to a raster file.

III

Airborne hyperspectral imaging of spatial soil organic carbon heterogeneity at the field-scale

modified on the basis of

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Submitted manuscript

1 INTRODUCTION

Soil organic carbon (SOC) is a particularly important soil property affecting other soil parameters as well as crop growth. The spatial distribution of the SOC content is often heterogeneous within agricultural fields. A detailed knowledge of the SOC content at the field-scale is required to support applications such as precision agriculture. Imaging spectroscopy in the visible (VIS) and near-infrared (NIR) region has proven to be highly sensitive to SOC and can efficiently provide data with high spatial resolution (Gomez et al., 2008; Stevens et al., 2010). As recently reported by Ben-Dor et al. (2009), Cécillon et al. (2009) and Ladoni et al. (2010), more experience is required to accurately predict SOC via airborne hyperspectral imaging, as only few studies dealt with this topic by now. Former research focused primarily on the detection of SOC at large regional scales for entire landscapes (Selige et al., 2006; Stevens et al., 2006, 2008, 2010). However, SOC can considerably vary within few meters. The objectives of this study were (i) to test the suitability of hyperspectral imaging (HyMap sensor) for the characterisation of the spatial heterogeneity of the SOC content at the field-scale including (ii) investigations concerning different soil surface conditions (roughness, vegetation) and (iii) to produce SOC maps for arable fields on a pixel-wise basis as required for precision agriculture.

2 MATERIAL AND METHODS

2.1 Study sites

The spatial variation of the SOC content was investigated at four agricultural fields in the Lower Rhine Basin in North Rhine-Westphalia, Germany. This region is characterised by a mean annual precipitation of 700 – 800 mm and a mean annual temperature of approximately 10°C. All test sites are covered by a loess layer (> 2 m) and have been under intensive and uniform cultivation for the last several decades. The distribution of SOC within the plough layer (0 – 30 cm) may be regarded as homogeneous due to annual ploughing, but ranges of SOC differed between the test sites (Tab. III.1). Due to different soil cultivation at the time of sampling, all test sites varied in surface roughness, soil structure and coverage with volunteered green crops and straw residues. Volunteer crops are crops which emerge from lost grains after harvest due to new germination. A fresh seed-bed was prepared a few days before sampling on Sinsteden BF (bare soil, fine seed-bed; 2.5 ha) test site, while the test site Sinsteden VC (volunteer crops; 9 ha) was harvested three weeks before sampling without subsequent cultivation. At Sinsteden VC, approximately 10% of the soil surface was covered by field bean residues and volunteers. Both other test sites at Oberhoicht belong to one arable field, where winter wheat was harvested three weeks before sampling. One part of the field was ploughed two weeks before sampling and thus not covered with straw residues (Oberhoicht PB: ploughed, bare soil; 3.5 ha), while the other part of the field was grubbed and covered to approximately 30% with straw residues (Oberhoicht GS: grubbed, straw residues; 3.5 ha). Dominant soil types of the two neighbouring test sites at Sinsteden (51°02'58" N, 6°38'38" E) are, according to the World Reference Base for Soil Resources (WRB; FAO, 2006), Cambisols, Regosols and Luvisols. The other two test sites, at Oberhoicht (50°36'57" N, 6°59'09" E), are dominated by Cambisols and Luvisols. While the within-field difference in altitude is similar on all test sites (Sinsteden BF, VC: 5.4 m; Oberhoicht PB, GS: 5.1 m), the sites at Sinsteden are indicated by a squared shape and a rather hilly relief with a slope of 3.5°, whereas the narrow, elongated test sites at Oberhoicht are plain (slope: < 1°). The test sites of 2.5 – 9 ha in size are in the typical range for agricultural fields in the study region and comparable to other small-scaled agricultural areas in Western Europe (e.g., 15 ha on average in Belgium; Sleutel et al., 2007).

Soil sampling took place on the 6th of August 2008, on the same day as the HyMap flight and aerial imaging campaign was performed. 500 g of soil were sampled from the upper 3 cm of the plough horizon in a radius of 2 m around randomly chosen sampling points at all test sites (n = 204). The spatial coordinates were recorded using differential GPS. The effects of varying soil moisture may be excluded in this study because the flight campaign was conducted after a period of dry weather which ensured uniformly dried soil surfaces. 44 soil samples were collected from Sinsteden BF test site, and 100 samples were taken from Sinsteden VC test site. Each 30 soil samples were collected from both Oberhoicht PB as well as from Oberhoicht GS test sites.

2.2 Conventional soil analyses

All soil samples were air-dried, passed through a 2 mm sieve and milled prior to analysis. Total C was analysed after dry combustion with an elemental analyser (Fisons NA 2000; ISO 10694, 1995). SOC was determined as total C minus inorganic C (Scheibler method).

2.3 Hyperspectral imaging in the VIS/NIR range

The reflectance properties varied between the test sites, as fields with different ranges of SOC and surface conditions were chosen for this study (Tab. III.1, III.2). The reflectance of the soil in the VIS/NIR range at the field-scale was recorded by the aircraft-mounted hyperspectral sensor HyMap (Integrated Spectronics, Sydney, Australia). The HyMap flight campaign was conducted by the German Aerospace Centre (DLR, Oberpfaffenhofen, Germany) on the 6th of August, 2008. HyMap uses a whisk-broom scanner with 512 pixels per line. It provides 126 spectral bands between 450 and 2500 nm. The bandwidths are dependent on the full width at half maximum (FWHM) of the spectral band, which is as follows: (i) 15 nm in the VIS (450 – 890 nm) and NIR (890 – 1350 nm), (ii) 13 nm in the SWIR1 (1400 – 1800 nm) and (iii) 17 nm in the SWIR2 (1950 – 2480 nm) ranges. A nominal spatial resolution of 4 m was achieved for each pixel at a flight level of 2000 m, which provides 625 pixels ha^{-1}. The data sets were radiometric calibrated and an atmospheric correction was carried out by the DLR using ATCOR4 to derive nadirnormalised ground reflectance.

For image processing of the HyMap spectra, the software package ENVI 4.7 (ITT Visual Information Solutions, Boulder, USA) was used. Spectra of four pixels (4 m by 4 m each) were consolidated and averaged to compensate for spatial offset in the HyMap data. Hence, the evaluated spectra evolve from an area of 8 m by 8 m (64 m^2).

2.4 Data treatment and statistical analyses

2.4.1 Partial least squares regression (PLSR)

Multivariate calibration using PLSR was conducted as outlined in section II.2 to calibrate the HyMap VIS/NIRS data with the reference SOC data from elemental analysis.

2.4.2 Image processing

A pixel-wise SOC map was prepared for one part of the Sinsteden VC test site to compare this form of data processing with geostatistical data processing, which is commonly used to reveal the spatial variation of a parameter. During image processing, spectra were calculated for each image pixel. Thereby, spectra from four pixel were selected using ENVI software and averaged. The prediction of the SOC content was performed using OPUS as described in section II.2.

2.4.3 Geostatistical data processing

Geostatistical data processing and the creation of maps were performed as described in section II.4.

3 RESULTS AND DISCUSSION

3.1 Prediction of SOC via airborne hyperspectral imaging

For the complete sample set, the SOC content ranged from 8.3 to 18.5 g SOC kg^{-1} (Tab. III.1), which is typical for arable fields in the study region (Preger et al., 2006). If data of all four test sites (n = 204) are combined, SOC can be predicted from the hyperspectral data with high accuracy. The coefficient of determination (R^2 = 0.83) as well as RMSEP (1.10 g SOC kg^{-1}), corresponding RPD (2.32) and RPIQ (4.41) corroborate the high quality of the calibration model (Fig. III.1). The modelling efficiency (EF) of 0.84 was high, indicating that the relative deviation of the predicted SOC values is almost as small as the variation in the lab data. The four test sites in this study are all derived from loess and reveal similar soil types. Stevens et al. (2010)

stated that calibrations based on soil types perform slightly better than those based on regions. In contrast to other studies, the SOC range of the present dataset was rather narrow. Stevens et al. (2006), e.g., partly included former grassland in their evaluation and thus reached a considerably higher SOC variability (8 – 58 g SOC kg^{-1}). Comparable SOC ranges can be found in several other studies (Selige et al., 2006; Gomez et al., 2008; Stevens et al., 2008, Wetterlind et al., 2008; Stevens et al., 2010). While in the present study only four test sites of relatively small size (2.5 – 9 ha) were investigated, most of the cited studies analysed regions comprising of several km^2.

Based on a wide SOC range (7 – 38 g SOC kg^{-1}) and large test sites (45 ha on average), Selige et al. (2006) achieved even better results (R^2 = 0.90, RMSECV = 0.29 g SOC kg^{-1}) with the HyMap sensor, while Patzold et al. (2008) obtained an R^2 of 0.74 and an RMSECV of 1.6 g SOC kg^{-1} with a very limited set of composite soil samples. Analysis with other hyperspectral airborne sensors in the VIS/NIR range and using PLSR calibration also achieved satisfactory results for the prediction of SOC (R^2 = 0.83 – 0.89; Ben-Dor et al., 2002; Stevens et al., 2006, 2010).

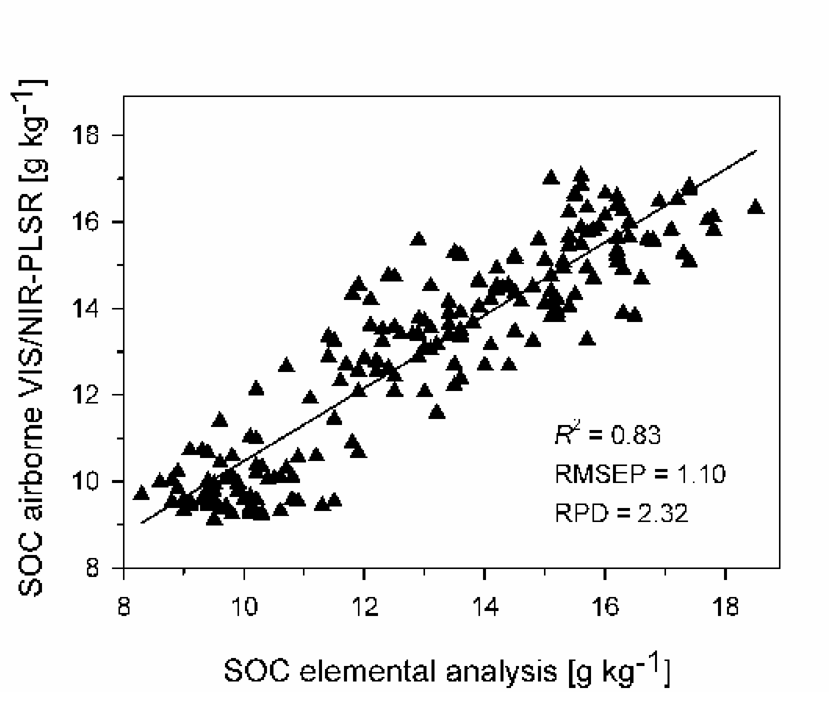

Fig. III.1: Regression of predicted versus observed SOC (g kg^{-1}) using the VIS/NIR spectral range for the complete sample set, depending on SOC values measured via elemental analysis (n = 204).

However, the presented results reveal the potential to predict SOC even at a comparatively small concentration range on long-term uniformly cultivated fields with a high accuracy using HyMap airborne spectroscopy.

3.2 Effects of soil surface conditions

Beside the influence of data range and field size, a further focus of this study was to demonstrate the effects of various surface conditions on airborne IR spectroscopy. Since the complete sample set involved different test sites and various surface conditions, the test sites were distinguished further to achieve this goal. While the effect of moisture content was negligible on the test sites due to dry soil surface conditions, the other mentioned factors potentially impacted the results. Both Sinsteden sites (BF, VC) revealed a rather even surface, but at Sinsteden VC no cultivation was performed after harvest and thus approximately 10% of the soil was covered by volunteer crops (field beans). Thus, the effect of plant coverage was studied in detail at Sinsteden test sites BF and VC with SOC concentration ranges from 8.9 – 15.4 g SOC kg^{-1} and 10.2 – 18.5 g SOC kg^{-1}, respectively, while the effect of tillage (i.e., roughness) was examined at Oberhoicht test sites PB and GS with comparatively narrow SOC concentration ranges (8.3 – 12.7 g SOC kg^{-1} and 9.1 – 11.9 g SOC kg^{-1}, respectively, Tab. III.1). Due to ploughing two weeks before sampling, no straw residues were present at Oberhoicht PB, while Oberhoicht GS test site was only grubbed and thus covered with approx. 30% of straw residues. In consequence, the effect of surface roughness could be examined at both Sinsteden BF and Oberhoicht PB test sites, while the effect of surface covering due to green vegetation and straw residues could be examined at both Sinsteden VC and Oberhoicht GS test sites.

At Sinsteden BF test site, a fresh seed-bed was prepared a few days before sampling, leading to almost optimal conditions for airborne reflectance spectroscopy due to low surface roughness and the absence of vegetation or straw residues. Thus, the accuracy of prediction based on site-specific calibrations performed best at this site with R^2 = 0.73, RMSEP = 0.76 g SOC kg^{-1}, RPD = 2.08 and RPIQ = 2.53 (Tab. III.1). Comparing Sinsteden VC, the lower prediction accuracy (R^2 = 0.61, RMSEP = 1.13 g SOC kg^{-1}, RPD = 1.63; RPIQ = 2.30; Tab. III.1) can be ascribed to the existence of volunteer crops affecting the spectral reflectance. At the ploughed Oberhoicht PB test site the prerequisites for IR measurements are still acceptable (R^2 = 0.53, RMSEP = 0.78 g SOC kg^{-1}, RPD < 1.41; RPIQ = 1.41; Tab. III.1). In contrast, the Oberhoicht GS test site represents the most unfavourable conditions: the surface was rough due to grubbing and, additionally, this cultivation left a cover with approximately 30% of straw residues. In consequence, this resulted in a prediction accuracy that did not match the above mentioned thresholds (e.g. EF = 0.30, RMSEP was not even predictable; Tab. III.1).

Compared to Sinsteden BF, ploughing at Oberhoicht PB produced a rougher surface, but this was consistent on the whole field. In addition, Oberhoicht PB site is characterised by a SOC range (9.7 – 12.7 g SOC kg^{-1}) which is significantly smaller than at Sinsteden BF site (8.9 – 15.4 g SOC kg^{-1}). It can be concluded that the slightly lower prediction accuracy at Oberhoicht PB can be ascribed to a low variation in the SOC range and at least partly to an increased roughness (Tab. III.1). Also Gomez et al. (2008) stated that a low variation of SOC contents can be a limiting factor for SOC prediction accuracy.

Besides the effect of SOC concentration ranges on calibration accuracy, the results indicate that prediction accuracy increases when only samples from fields without vegetation or crop residue cover are taken into account. A sparse vegetation residue of 10% from volunteer crops (Sinsteden VC) without subsequent tillage leaves 90% of the soil bare and available for reflectance. The precision was affected even more strongly by grubbing after the harvest of cereals which leaves a coverage of 30% of straw residues (Oberhoicht GS). Additionally, emerged green plants have a spectral reflectance rather different from SOC, while straw residues reveal reflectance properties similar to SOC and thus severely affect the calibration model. This assumption was already reported by Serbin et al. (2009) and is confirmed by the presented results. However, reports in the literature regarding the effect of vegetation cover on the evaluation of (hyper-) spectral data are inconsistent. Bartholomeus et al. (2007, 2010) showed that even a vegetation cover of 5% leads to large variations in the estimation of soil properties such as iron content and SOC, while Chabrillat et al.

Tab. III.1: Model parameters and prediction quality of airborne VIS/NIR spectroscopy for SOC

Calibration set	SOC (g kg^{-1}) Mean	Min	Max	SD[a]	R^2	RMSECV[b] (g kg^{-1})	RPD[c] (cross val)	RMSEP[d] (g kg^{-1})	RPD[e] (test-set val)	RPIQ[f] (test-set val)	BIAS (g kg^{-1})	EF[g]	LV[h]
complete data set (n = 204)	13.0	8.3	18.5	2.6	0.83	1.05	2.45	1.10	2.32	4.41	0.02	0.84	7
site-specific subsets													
Sinsteden BF (n = 44)	13.0	8.9	15.4	1.5	0.73	0.76	1.91	0.76	2.08	2.53	0.01	0.73	5
Sinsteden VC (n = 100)	14.9	10.2	18.5	1.8	0.61	1.09	1.59	1.13	1.63	2.30	2.24	0.60	6
Oberhoicht PB (n = 30)	9.7	8.3	12.7	0.9	0.53	0.62	1.46	0.78	1.14	1.41	2.72	0.53	3
Oberhoicht GS (n = 30)	10.1	9.1	11.9	0.6	0.34	0.51	1.19	n.p.[i]	n.p.[i]	n.p.[i]	0.30	0.30	2

[a] standard deviation.
[b] Root mean square error of cross validation.
[c] Ratio of performance to deviation for cross validation.
[d] Root mean square error of prediction for test-set validation (30%).
[e] Ratio of performance to deviation for test-set validation.
[f] Ratio of performance to interquartile distance for test-set validation.
[g] Modeling efficiency.
[h] Number of latent variables used for prediction.
[i] Test-set validation was not predictable.

(2002) reported that clay minerals can still be satisfactorily detected with a dry vegetation cover of 20 – 30% and a green vegetation cover of 40 – 50%.

Several studies revealed that mainly surface roughness, moisture content of the soil surface as well as vegetation or crop residues may affect the prediction accuracy of hyperspectral images (Ben-Dor et al., 2002; Stevens et al., 2006, 2008; Cécillon et al., 2009). The prediction accuracy of spectroscopic measurements in the field is often less precise than under laboratory conditions (Chang et al., 2001). However, under specific conditions (flat surface, homogeneous texture, low variability in moisture content, absence of vegetation) portable or airborne spectroscopy can be equivalent to laboratory conditions (Stevens et al., 2008).

The effects of various surface covers became also visible in the spectral ranges that were selected for prediction models on different test sites. Data processing and spectral ranges used in the prediction models as selected by OPUS software are displayed in Table III.2. While the complete data set involves almost the whole spectral range from 539 to 2477 nm (including interruptions based on the PLSR procedure via OPUS, cf. 2.4.1), the spectral ranges clearly differed between the individual test sites. At Sinsteden BF test site, the OPUS software incorporated mainly VIS (400 – 700 nm) and SWIR1 (1200 – 1900 nm) in the prediction model, while wavelengths from all spectral ranges mainly formed the prediction models at Sinsteden VC and Oberhoicht PB. Particularly at Sinsteden VC, where approximately 10% of the soil surface was covered by volunteer field beans, parts of the VIS range were selected by OPUS to achieve an optimum SOC model. Thus, it seems that chlorophyll absorption bands (between 430 and 660 nm) contributed to the SOC calibration model at this test site. As recently revealed by Bartholomeus et al. (2010), vegetation cover strongly affects the prediction accuracy of SOC based on PLSR. Therefore, model parameters at Sinsteden VC indicate a slightly worse SOC prediction compared to Sinsteden BF (Tab. III.1).

However, various authors found different spectral ranges as crucial for the prediction of SOC via VIS/NIRS. Henderson et al. (1992) considered the whole range between 405 and 1055 nm (VIS, NIR) when analysing soil properties which are dominated by

SOC content. They also considered several wavelengths between 1065 and 1165 nm (NIR) as well as between 1955 and 2495 nm (SWIR2) as significant for SOC. According to the review of Bellon-Maurel and McBratney (2011), the spectral range between 1650 and 2500 nm is crucial for SOC prediction. Viscarra Rossel and Behrens (2010) noted that most organic soil constituents are characterised by CH, CO and OH stretching combinations in the NIR, SWIR1 and SWIR2. According to Serbin et al. (2009), the spectral reflectance of soil is very similar to that of dead straw residues in the VIS, NIR and SWIR1. In contrast, at Oberhoicht GS test site (30% straw residues), only the upper part of SWIR1 and the entire SWIR2 had an effect on the prediction model, whereas the VIS region, containing the chlorophyll bands, was not included in the model (Tab. III.2). Thus, it is difficult to distinguish between straw residues and SOC via reflectance spectroscopy in the VIS/NIR. This may explain the low prediction accuracy of SOC at Oberhoicht GS. Linear spectral unmixing (Yang et al., 2007; Martínez et al., 2010) or residual spectral unmixing (Bartholomeus et al., 2010) seem

Tab. III.2: Data processing and spectral ranges used in PLSR prediction models for the complete data set and subsets for each individual site

Calibration set	Surface conditions	Data processing	Spectral range (nm)
complete data set (n = 204)		No data processing	539-2477
site-specific subsets			
Sinsteden BF (n = 44)	bare soil, fine seed-bed	No data processing	592-694 760-902 1287-1755
Sinsteden VC (n = 100)	10% of volunteer crops (field beans)	No data processing	539-607 675-784 869-2477
Oberhoicht PB (n = 30)	ploughed, bare soil	Multiplicative scatter Correction	675-902 784-1755 2055-2477
Oberhoicht GS (n = 30)	grubbed, 30% of straw residues	First derivative	1636-2477

to be useful tools to solve the problem of mixed pixels which occurred at Sinsteden VC and Oberhoicht GS. However, related data processing procedures were not the focus of this study, but they will be pursued and addressed in future research.

Relevant spectral information can be discovered from the latent variables of the PLSR model (Janik and Skjemstad, 1995). Especially the loading weights of the first latent variable allow for chemical and structural interpretation of spectral features. For the complete data set in this study, the loading weights of the first latent variable reveal several chemical characteristics belonging to different SOC constituents (Fig. III.2). These findings mostly conform to results found in the literature, where various authors found different wavelengths responsible for SOC in the reflectance spectra of soils (Henderson, 1992; Brown et al., 2006; Viscarra Rossel et al., 2006; Viscarra Rossel and Behrens, 2010).

According to Haaland and Thomas (1988), positive peaks generally correspond to the component of interest and negative peaks relate to interfering components. Thus, the positive peaks in the first loading weight can mainly be addressed to major signals of organic soil components (Fig. III.2). Brown et al. (2006) stated the small peak at 540 nm as a reflection of SOC. Additionally, the adjacent shoulder between 530 and 570 nm is an important region for the prediction of SOC in general (Viscarra Rossel et al., 2006). Also amines (751 nm) and alkyl compounds (1754 nm) contribute to the prediction of the SOC content (Viscarra Rossel and Behrens, 2010). The high peak of the first loading weight at 1358 nm can be addressed to a C-H bond of methyl and belongs to aliphatic carbon (Workman and Weyer, 2008). Henderson et al. (1992) found the region between 1125 and 1165 nm as responsible for SOC, and Viscarra Rossel and Behrens (2010) detected alkyl compounds at 1170 nm. In the presented data model, only a small shoulder around 1162 nm was observable beside other dominating signals. Henderson et al. (1992) observed soil properties that mask SOC effects between 2225 and 2255 nm. Thus, the peak at 2245 nm cannot be ascribed to SOC and may be a contribution of volunteer crops and straw residues affecting the prediction model of the complete data set (Serbin et al., 2009).

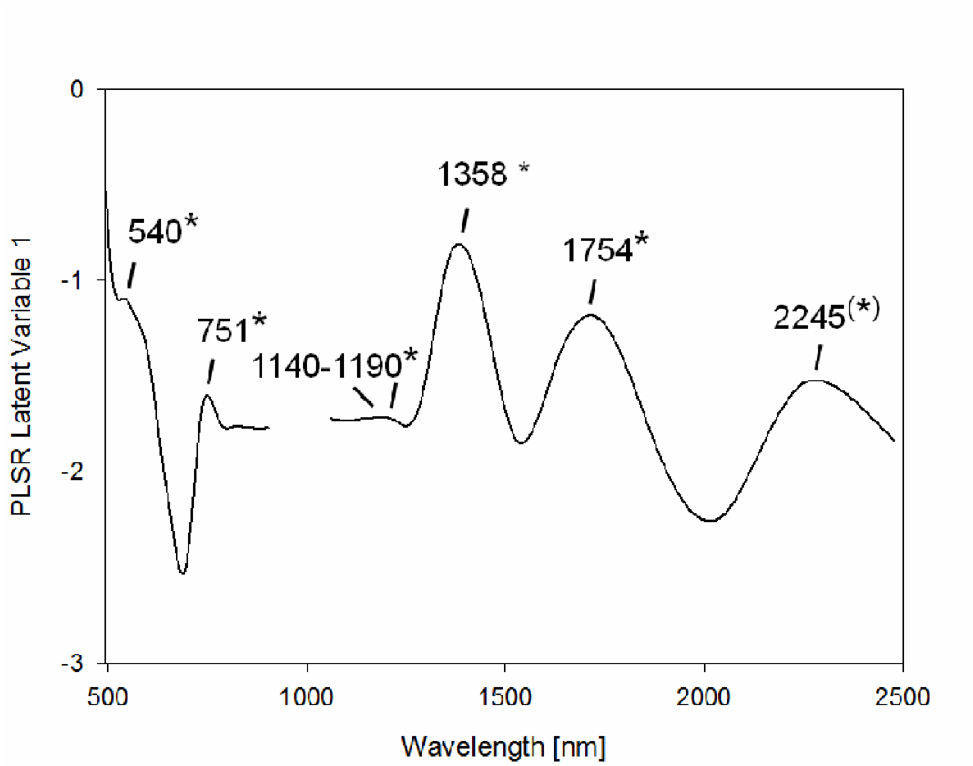

Fig. III.2: Loading weights of the first latent variable of the PLSR prediction model for SOC content (g kg^{-1}) in the complete data set (n = 204). Positive peaks marked with stars (*) reveal chemical characteristics belonging to distinct SOC constituents conformed to results found in literature.

Published data pointed out that different wavelengths can contribute to the SOC prediction. Besides parent material and texture, complex molecular structures of SOM result in diverse NIR reflectance spectra. Moreover, different soils, sensors and measuring conditions create widely varying reflectance results. Thus, not all loading weights presented in Figure III.2 can be distinctly nor positively identified. In contrast, loading weights were successfully used for the interpretation of MIR spectra (Janik and Skjemstad, 1995; Bornemann et al., 2008), while it currently seems uncommon to present loading weights in the case of VIS/NIRS analyses. This may be due to many overlapping combinations and overtones which are caused by NH, CH and OH vibrations (Chang et al., 2001; Chang and Laird, 2002; Viscarra Rossel et al., 2006; Reeves, 2010).

For the site-specific subsets, consistent wavelengths as well as wavelengths whose attributions were not possible were observed (data not shown). As already shown in

Table III.2, specific spectral ranges can be responsible for the prediction of the SOC content. However, modulated by the varying surface conditions, overall satisfactory results were achieved to estimate the SOC content at the field-scale via hyperspectral imaging. Accordingly, Stevens et al. (2006, 2010) stated that calibration modelling has to be performed before each field campaign when soil texture varies widely, because the reflectance of the soil varies with local circumstances of the soil. In a next step, the presented results were used to produce SOC maps with high accuracy at the field-scale.

3.3 Enhancing spatial resolution of soil mapping

One prerequisite for precision agriculture is the exact knowledge of soil properties at the field-scale. Thus, well-defined management zones are required for a site-specific management. Maps containing management zones can help farmers to optimise site-specific management decisions, such as the adaption of the applied amount of fertilisers, herbicides or pesticides to site-specific conditions. The SOC content is an important parameter for this purpose, because SOC affects the behaviour of fertilisers, herbicides and pesticides in soil (Wauchope et al., 2002; Patzold et al., 2008; Ladoni et al., 2010). Due to its spatial resolution and editing of pixels with a definite size, hyperspectral imaging should be a novel basis to create SOC maps for site-specific management.

Field maps of different soil properties are often based on a limited number of point measurements and are mostly generated via GIS interpolation techniques like IDW or kriging (Ben-Dor et al., 2002; Odlare et al., 2005; Bilgili et al,. 2010). Such interpolations can lead to a smoothing of the given heterogeneity. To test this, a reference SOC map via ordinary kriging was generated on the basis of 100 sample points at Sinsteden VC test site (Fig. III.3a). Then, a SOC map without interpolation, but on a pixel-wise basis for one part of the field was produced, marked in Figure III.3a. All pixels of the part under study (each 64 m^2) were selected, based on 4 raw-data-pixels each, and a prediction model via PLSR on the basis of the site-specific calibration model was created, resulting in a very detailed and specific map of the SOC content (Fig. III.3b). The pixel-based map allows for detecting the small-scale

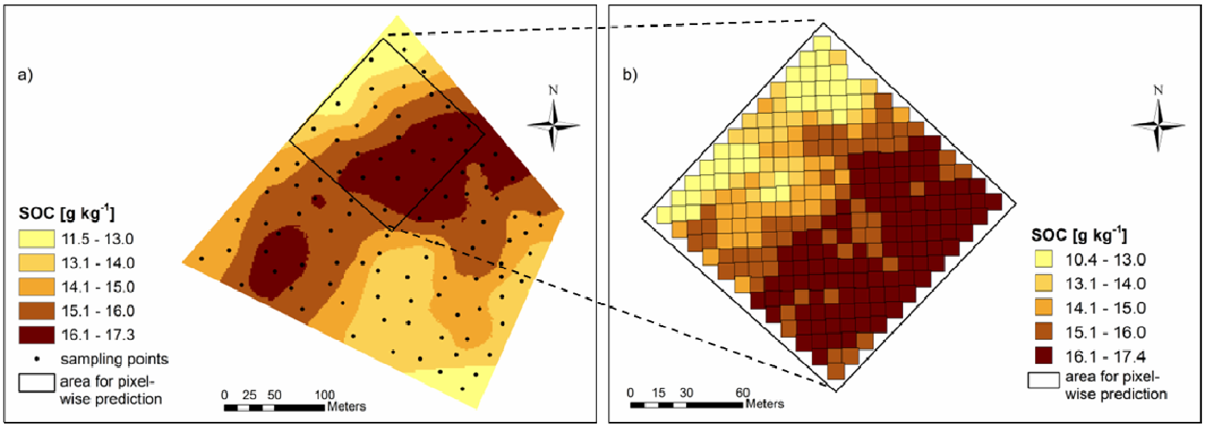

Fig. III.3: SOC maps of Sinsteden VC test site: a) kriged SOC map of the whole test site based on data from elemental analysis (n = 100); b) detailed view from a part of the test site with pixel-wise prediction of SOC, based on the most robust prediction model using the VIS/NIR spectral range (n = 264).

variability of SOC contents more realistically than the interpolated map. The interpolation actually smoothes the spatial variability of SOC contents and neglects several small-scale variations.

A pixel-wise map as generated for the SOC content in this study should be practicable for the use within the scope of precision agriculture. The working width of agricultural equipment such as sprayers is often between 16 and 24 m, including the use of part width sections. Thus, a too detailed SOC map reflecting each pixel is not as useful for practical farming as a SOC map containing management zones of at least 8 m. With a map as presented in this study, site-specific herbicide application is possible with a multiple sprayer as presented by Dicke et al. (2007).

Other authors noted that such pixel-wise maps can also help to verify the effects of land-use changes on the SOC content of agricultural areas (Selige et al., 2006; Stevens et al., 2006, 2010). Ben-Dor et al. (2009) stated that the high quality of imaging spectroscopy is important for the quantitative assessment of SOC and soil C monitoring. The HyMap sensor enables a satisfactory pixel-by-pixel resolution. Hence, the presented method may improve geostatistical data processing in conducting precision agriculture.

In agricultural soils, a significant spatial heterogeneity of SOC occurs at the field-scale, although land management has been uniform over several decades (Odlare et al., 2005; Patzold et al., 2008). On agricultural fields with a uniform parent material the spatial variability of SOC can mainly depend on the land surface relief and topography as well as on former land management systems or hedges. This relation is displayed exemplarily for two test sites in Figure III.4. The within-field difference in elevation was higher at Sinsteden VC test site (Fig. III.4a) than at Oberhoicht PB (Fig. III.4b). This is probably related to soil erosion and colluviation and, in consequence, one reason for variances in the SOC content. The effect of the relief on the spatial distribution of SOC became clearly visible at Sinsteden VC, where the highest SOC contents occur in the lower, depressed areas and *vice versa*. However, even the generally low slope at Oberhoicht PB affected the distribution of SOC in the same way. De Gryze et al. (2008) and Stevens et al. (2010) found similar relations between relief and spatial distribution of SOC. De Gryze et al. (2008) stated a strong relationship between SOC content and transport of sediments by erosive processes

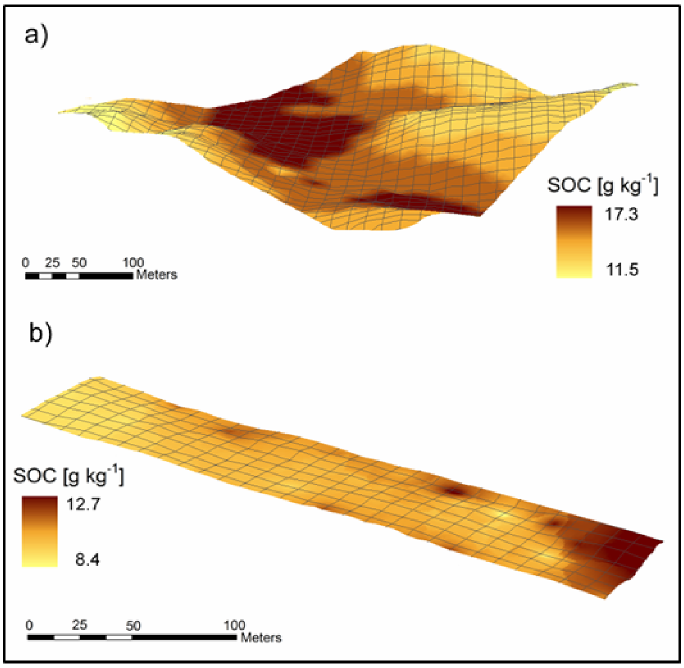

Fig. III.4: Maps of a) Sinsteden VC test site and b) Oberhoicht PB test site, showing interpolated SOC contents (g kg^{-1}) related to topography (slope at Sinsteden VC: 3.5°, slope at Oberhoicht PB: < 1°).

under conventional tillage. They concluded that topographic aspects of agricultural fields and their interactions with management should be taken into account when calculating soil nutrient demand or organic carbon content. Ben-Dor et al. (2009) stated that hyperspectral imaging and resulting soil maps have great potential for monitoring soil erosion and degradation processes.

Precise SOC maps including topographic and management information may be useful to determine whether agricultural land is a source or sink for carbon. In this context, Smith (2004) addressed that a new elaborate sampling scheme is essential to measure changes in SOC over a period of 5 years as required in the Kyoto Protocol. A five-to ten-year sampling interval is also required by soil monitoring programs for an early detection of changes in soil quality over space and time (Cécillon et al., 2009). Shepherd and Walsh (2002) suggested spectral libraries for the prediction of soil properties. They successfully predicted SOC using a library containing over thousand soils from Africa, while Brown et al. (2006) could not predict SOC with an acceptable accuracy for most applications using a diverse library of soil samples for spectral analyses from all over the world. Stevens et al. (2008) concluded that such global spectral libraries can be used to classify measured spectra and only a part of the library may be used for prediction. Very recently O´Rourke and Holden (2011) stated that the use of imaging spectroscopy and chemometric methods can be an alternative to conventional laboratory analysis due to lower costs, a greater number of samples and a higher spatial resolution. Based on the presented results it is suggested that periodical hyperspectral airborne measurements could be conducted on representative agricultural fields under the same surface conditions, which are typical for specific landscapes. Subsequent regional spectral libraries should be generated in consideration of varying soil types and texture. Furthermore, spectral libraries, which take varying soil surface conditions into account, might help to further improve high-resolution SOC predictions. The combination of these methods may become a new approach in soil C monitoring and for precision agriculture purposes.

4 CONCLUSIONS AND PERSPECTIVES

The results reveal that airborne hyperspectral imaging is a promising tool used to detect the variability of SOC content even at a comparatively small concentration range on long-term uniformly cultivated fields at a small spatial scale with high accuracy. After the necessary local calibrations are made, more precise results can be achieved than with regional calibrations, especially with varying surface conditions. The pixel-wise prediction of SOC in field maps without the need of geostatistical treatment seems especially reasonable for precision agriculture practices and soil C monitoring. It can be further concluded that site-specific SOC maps based on hyperspectral imaging may be provided for precision agriculture purposes when SOC information is needed at a resolution that meets the working widths of agricultural machinery. At the present levels of technology and state of the art equipment, airborne hypersectral imaging provides SOC information with an accuracy comparable to conventional sampling and subsequent analysis, but at an improved scale of several m^2.

Future research should focus on the reduction of the effect of green vegetation and straw residue covers using methods such as linear spectral unmixing. The prediction accuracy on neighboured fields in consideration of soil texture and surface conditions should also be further improved. With respect to soil C monitoring it could be useful to focus on building spectral libraries for different regions, soil types, textures and surface conditions.

IV

Soil heterogeneity as evaluated by apparent electrical conductivity affects the patchiness of *Heterodera schachtii* within sugar beet fields

modified on the basis of

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1 INTRODUCTION

The beet cyst nematode (BCN), *H. schachtii*, causes severe yield losses in sugar beet production worldwide (D'Addabbo et al., 2005). Frequently, infested fields are characterised by an uneven, patchy distribution of the nematode (Cooke, 1987). Soil texture is often regarded as the dominant soil property affecting the variable population density of *H. schachtii* (Wallace, 1968; Schmidt et al., 1993). However, there are few detailed studies about the spatial distribution of *H. schachtii* within fields (Hillnhütter et al., 2011a). Mainly greenhouse experiments have shown that soil temperature and moisture, which are both closely related to texture, have a major effect on the development of the BCN population and also on the sugar beet yields (Raski and Johnson, 1959; Santo and Bolander, 1979; Griffin, 1988). Therefore, it seems reasonable to study the relationship between soil texture and the spatial variability of *H. schachtii* population density at the field-scale.

Conventional soil sampling to determine texture and nematode populations is laborious and expensive (Nutter et al., 2002; Avendaño et al., 2003). Measures to control BCN do not usually account for soil heterogeneity or for the patchy occurrence of BCN. Moreover, usual management strategies treat arable fields uniformly by applying one or more of the following methods: application of nematicides (depending on national regulations), cultivation of tolerant and / or resistant sugar beet cultivars, intercropping and crop rotation with catch crops such as resistant mustard or oil radish (Schlang, 1991; Heinicke and Warnecke, 2006).

Precision agriculture aims at a site-specific management of different zones within entire fields. Targeted BCN control needs high-resolution soil information as a prerequisite to such management because of BCN's patchy occurrence (Sommer et al., 2003; Hillnhütter and Mahlein, 2008). Against this background, the apparent electrical conductivity (EC_a), which is known to be strongly related to soil texture, was measured in four agricultural fields using the non-invasive EM38 sensor; two textural homogeneous and two textural heterogeneous fields were studied. The aim of this study was to demonstrate that maps of soil texture based on EC_a measurements – when used in combination with additional soil data – might provide a solid basis for site-specific BCN management.

2 MATERIAL AND METHODS

2.1 Research fields

The spatial variation in soil texture and population density of *H. schachtii* was investigated in four agricultural fields of a traditional sugar beet production area in the Lower Rhine Basin (North Rhine-Westphalia, Germany). All fields were chosen because they were known to be infested with *H. schachtii* and traditional soil information as well as previously measured EC_a data were available. The fields belong to private farmers who selected the cultivars to be sown. The field size varies between 3 and 10 ha. Within these fields, test plots of 0.5 – 1.2 ha were selected and analysed. Before soil sampling took place, the EC_a was recorded to obtain an overview of the textural heterogeneity of the fields. Detailed information about the research fields are given in Table IV.1.

2.2 Measurement of the apparent electrical conductivity (EC_a)

EC_a of the research fields was measured as described in section II.3.

Tab. IV.1: Description of the research fields

Research fields	Northing	Easting	Mean annual precipitation (mm)	Mean annual temperature (°C)	Soil type[a]	Cultivar
Altendorf	50°37`	6°59`	600	9.2	Haplic Luvisols	Beretta[b]
Billig	50°38`	6°46`	600	9.2	Haplic Cambisols	Beretta[b]
Elmpt	51°12`	6°09`	770	9.6	Plaggic Cambisols	Beretta[b]
Palmersheim	50°37`	6°52`	600	9.2	Stagnic Luvisols, Haplic Stagnosols	Pauletta[c]

[a] soil types according to the World Reference Base for Soil Resources (WRB, FAO, 2006).
[b] susceptible to BCN.
[c] tolerant to BCN.

2.3 Soil sampling

Sampling on a regular grid with a narrow vertical spacing is an appropriate method to determine nematode population densities (Been and Schomaker, 1996; Nutter et al., 2002). Conventional sampling designs are expensive and time-consuming; therefore, other sampling schemes were chosen to study the correlation between soil texture and spatial variation of the *H. schachtii* population density in the four fields. Sampling at Elmpt, Billig and Altendorf fields was along transects, whereas a nested sampling scheme was adapted for Palmersheim field. Elmpt and Billig fields were sampled a few days before the sugar beet harvest in October 2008, and Altendorf field was sampled a few days after the sugar beet harvest in October 2009. Sampling along selected transects covered, if present, the heterogeneity of the EC_a values. About 40 – 50 sampling points were chosen in each of the fields.

To create maps of the spatial variation in fields requires sampling of the soil at a scale that reflects the scale of that variation. As little prior information about the scale of variation was available, the nested sampling design of Avendaño et al. (2003), which was adapted from that of Webster and Boag (1992), was performed. The sampling was done one month after the sugar beet harvest in November 2008 at the Palmersheim field. The field was divided into 14 plots of 30 × 30 m; this formed the first level of the hierarchy. Ten samples were taken in each plot (n = 140) following Avendaño et al. (2003). Within the plots, at the second level, there were two sampling points 16.7 m apart and on random orientations from each other. From each of these two samples, sampling followed an almost 3-fold progression to 5.6, 2.7, 0.6 and 0.2 m (Fig. IV.1) and all locations were selected along random orientations from the previous sampling point. The spatial coordinates of the sampling points were recorded using differential GPS.

Background information from soil maps based on soil taxation with the largest scale is available ('Bodenkarte auf der Grundlage der Bodenschätzung' 1:5000; Mückenhausen and Mertens, 1960) and the EC_a data were taken into consideration to select the soil sampling points. Blum et al. (2005) describe in full the origin of soil taxation maps for Austria, which conforms to the German soil survey taxation map.

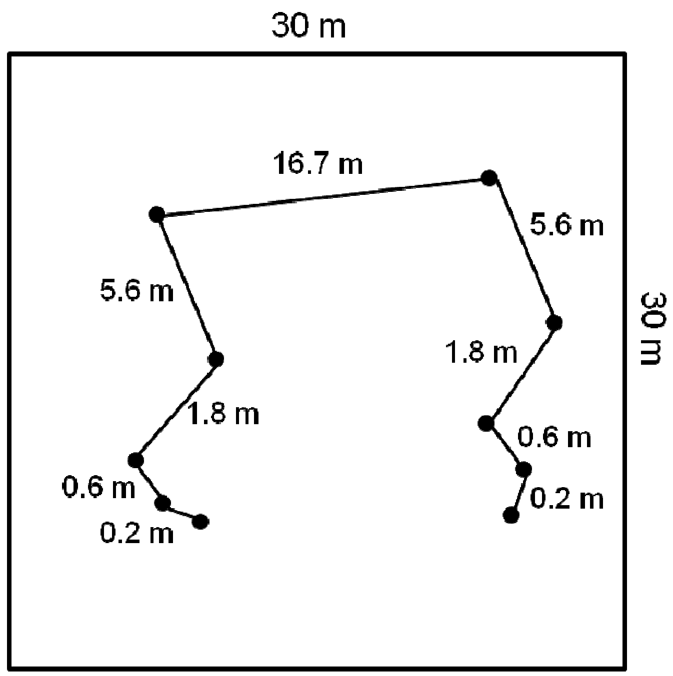

Fig. IV.1: Nested sampling design used for soil sampling in each sampling plot (30 × 30 m each) at Palmersheim field, adapted from Webster and Boag (1992) and Avendaño et al. (2003).

These maps were originally created to estimate the earning potential from agricultural land and include information about soil texture, parent material and the so-called soil quality index. The soil quality index from soil taxation maps is an indicator of crop productivity for German soils with a maximum value of 100 for most productive soils. The accuracy of the traditional soil taxation maps was verified by own surveys. Therefore, based on the soil taxation maps, 'deep' (> 80 cm), 'shallow' (50 – 80 cm) and 'very shallow' (20 – 50 cm) soils were classified according to the parent material.

At each sampling point three sub-samples were taken from an area of a few dm (< 0.3 dm) in the root zone using an auger (0 – 25 cm) and bulked to obtain 1.5 – 2.0 kg soil, which is the amount needed to determine the nematode population density (Been and Schomaker, 1996). Soil samples were stored at 4°C until the cysts were extracted. Soil texture was determined on air-dried subsamples.

2.4 Determination of soil texture

Soil texture of the air-dried, sieved (< 2 mm) and milled samples was evaluated using MIRS-PLSR. Subsamples of 20 mg were taken for the calibration procedure, which is described in detail in section II.2. The model used for calibration was based on 150 soil samples from a regional study of arable fields in North Rhine-Westphalia, which covered the dominant substrates and texture classes of the region (unpublished project report). The texture of these 150 samples was determined by a combination of wet sieving (sand fractions) and sedimentation (silt and clay fraction) after Köhn (ISO 11277, 2002) on subsamples of 20 g.

2.5 Evaluation of *Heterodera schachtii*

Cysts of *H. schachtii* were extracted from 300 ml of soil for each sample by the wet-screen decantation technique on a sieve combination of 500 and 100 µm mesh. The cysts were separated from soil organic matter using the density centrifugation method with a 9.97 M magnesium sulphate solution (Müller, 1980, 1988). The number of cysts per sample were counted under a stereoscope and transferred to 15 ml homogenisation tubes (B. Braun, Melsungen, Germany), where the cyst walls were crushed to free the eggs and J2. The number of eggs and J2 per sample was counted under a microscope with a 2 ml RAS-counting slide (Hooper et al., 2005). The number of cysts and number of eggs and J2 were referred to 100 g of soil to describe the *H. schachtii* population density in relation to the soil mass.

2.6 Geostatistical data analysis

The intensive sampling enabled the performance of the variogram of geostatistics (Webster and Oliver, 2007). The variogram summarises the way that a property varies spatially. The experimental variogram was modelled in GenStat (Payne, 2008) to obtain the parameters required for geostatistical prediction, kriging. Ordinary kriging was done in ArcGIS Editor 9.3 (ESRI, Redlands, California, USA) to predict the nematode density and EC_a on a fine grid of 5×5 m for mapping their distribution in the fields investigated.

3 RESULTS AND DISCUSSION

Relationships between soil texture and related soil properties and the population density of *H. schachtii* were determined with EC_a measurements. First, the spatial variation in soil texture as predicted by EC_a was analysed, and thereafter the effect of soil texture on the population density of *H. schachtii* was assessed. Management maps based on these results for potential site-specific management of BCN were created.

3.1 Spatial variation of soil texture as predicted by EC_a

The repeated measurements by EM38 revealed that apparent electrical conductivity (EC_a) values differed only slightly over time. The general spatial pattern in EC_a within the test fields remained quite stable, which conforms to other results (Sudduth et al., 2001; Mertens et al., 2008). Therefore, the effect of variable soil moisture and temperature can be regarded as negligible in this case.

The level and range of EC_a values vary considerably between fields (Tab. IV.2). The smallest EC_a was measured at Elmpt field (average 3.8 mS m^{-1}). The average EC_a values for each of the other three fields were much larger, but quite similar to one another (17.2 – 19.2 mS m^{-1}). The range of EC_a values within these fields, as well as the standard deviation, differ markedly, increasing in the order Altendorf < Billig < Palmersheim (Tab. IV.2).

Tab. IV.2: Apparent electrical conductivity (EC_a, mS m^{-1}) and predicted mean textural classes of the varying test sites

Research fields	EC_a (mS m^{-1})				Clay (g kg^{-1})		Silt (g kg^{-1})		Sand (g kg^{-1})	
	Min	Max	Mean	SD[a]	Mean	SD[a]	Mean	SD[a]	Mean	SD[a]
Elmpt	1.5	6.0	3.8	0.7	39	15.0	435	58.6	561	43.5
Altendorf	14.2	19.2	17.2	1.2	152	17.2	767	51.4	81	47.1
Billig	11.3	26.0	19.2	4.0	140	14.4	682	44.2	184	53.5
Palmersheim	8.0	36.0	17.8	6.1	156	22.0	694	107.6	118	44.4

[a] SD = standard deviation.
Note: Sum of percentage of soil texture fractions can deviate from 100, because each fraction was separately predicted by MIRS-PLSR on the basis of individual calibration models for clay, silt and sand.

The measured EC_a values of the different fields correspond to the arithmetic average of the texture data as predicted by MIRS-PLSR (Tab. IV.2). Nevertheless, it should be noted that EC_a integrates information on soil texture over the whole rooting depth (1.5 m), whereas soil sampling to determine the texture was done only in the plough horizon. Thus, the two approaches provide different informations concerning soil texture and depth; both are of significant interest for the development of BCN as discussed below. The small EC_a values in Elmpt field coincide with the largest sand (561 g kg^{-1}) and smallest clay contents (39 g kg^{-1}) in the sampled topsoil. The other fields are dominated by silt and have a mean clay content of about 150 g kg^{-1}. Thus, EC_a data can be associated with differences in soil texture, which has also been observed by several other studies (e.g. Domsch and Giebel, 2004; Sudduth et al., 2005).

Carroll and Oliver (2005) and Mertens et al. (2008) indicated that the benefit of EC_a values might be that they accord with the general pattern of textural heterogeneity within a field rather than providing an absolute measure for a particular soil property. Therefore, if maps of EC_a indicate spatial variation in the soil, they can be used to identify management zones for crop protection (Patzold et al, 2008) and to target site-specific soil sampling (Carroll and Oliver, 2005). As suggested by Kühn et al. (2009a), the interpretation of EC_a data can be improved by using additional geological or geomorphological information. Mertens et al. (2008) recommended a combination of EC_a and traditional soil taxation maps to improve the accuracy and validity of soil information and to compensate for the missing depth resolution of EC_a data. Therefore, information from soil taxation maps (1:5000) was taken into consideration and adapted to the WRB classification system. According to these maps, Elmpt field is characterised by deep soil (Plaggic Cambisol) with light texture (sandy loam) and Altendorf field also has a deep soil (Haplic Luvisol) with medium texture (silt loam). The EC_a data for these fields have the narrowest ranges and smallest standard deviations (0.7 and 1.2 mS m^{-1}, respectively, Tab. IV.2), which indicate little spatial variation in soil texture.

The other two fields are more heterogeneous. Billig field has partly shallow and deep soil (Haplic Cambisol) with medium texture (silt loam). Palmersheim field is characterised by the deep Stagnic Luvisol and the shallow Haplic Stagnosol, both a moderately clayey silt (medium texture) according to the German Soil Classification (Ad-hoc-AG Boden, 2005), and the shallow to very shallow Haplic Stagnosol, a strong clayey silt (heavy texture). In both these fields the spatial heterogeneity revealed by the soil taxation maps conforms to the spatial distribution of EC_a data with the largest standard deviations (Billig 4.0 and Palmersheim 6.1 mS m^{-1}, Tab. IV.2). The additional information from soil taxation maps also supported the interpretation of BCN results (see below).

3.2 Effect of soil texture (EC_a) on the population density of *Heterodera schachtii*

In early studies dealing with the population density of *H. schachtii*, both the number of cysts and the number of eggs and J2 were counted (Wallace, 1956; Thomason and Fife, 1962). The number of eggs and J2 per mass unit of soil is the property recommended in studies dealing with the determination of economic threshold levels for *H. schachtii* (Müller, 1980; Griffin, 1981a). Thus, recent studies mostly refer to the number of eggs and J2 when dealing with the population dynamics of plant parasitic cyst nematodes (Westphal and Becker, 2001; Nutter et al., 2002; Hillnhütter et al., 2011b). In contrast, Todd and Pearson (1988), Francl (1993) and Avendaño et al. (2003, 2004) achieved reliable results in their studies by observing the effect of soil properties on the population density of *Heterodera glycines* when counting cysts as well as eggs and J2. It seems that the property of interest depends on the focus of the research.

In the current study both the number of cysts and the number of eggs and J2 were counted to observe the population dynamics of *H. schachtii*. The results of both properties differed from each other. Also, statistical relationships between the number of cysts and number of eggs and J2 varied considerably between fields (R^2 = 0.12 – 0.65, data not shown). Consequently, the number of eggs per cyst was also very variable and thus not a useful property to determine the spatial heterogeneity of BCN, which corresponds with the results of Griffin (1981a) and Avendaño et al. (2003). Therefore, the focus of this study was applied on the number of eggs and J2 as well as on the number of cysts of *H. schachtii*.

3.2.1 Relation between EC_a and the number of eggs and J2

The relationships between EC_a data and the number of eggs and J2 are shown in Figures IV.2a – d. If they are considered separately, none of the four fields shows a relation between EC_a and the number of eggs and J2 of *H. schachtii*. At Palmersheim field (Fig. IV.2d) there is a slight trend with more eggs and J2 at the smaller EC_a values, but the relation is not statistically significant. However, a relationship can be recognised regarding all data; the largest number of eggs and J2 per 100 g soil, up to 25,000, occurs in Elmpt field (Fig. IV.2a), where the light texture (sandy loam) corresponds with small EC_a values (Tab. IV.2). The other fields with medium to large EC_a are characterised by much smaller nematode numbers (up to

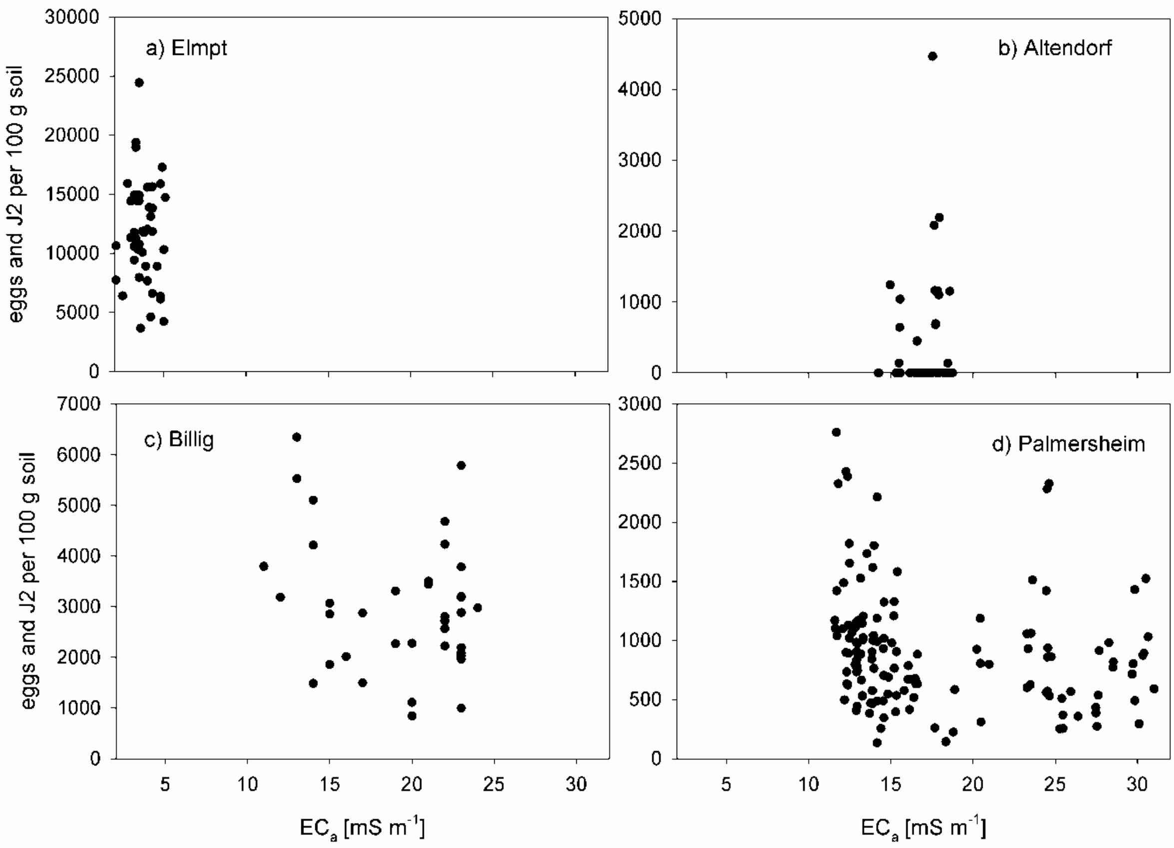

Fig. IV.2: Relationship between the EC_a values ($mS\ m^{-1}$) and the number of eggs and J2 of *H. schachtii* per 100 g soil at fields a) Elmpt (n = 50), b) Altendorf (n = 46), c) Billig (n = 40) and d) Palmersheim (n = 140). Note the different scaling of the y axes.

6345 eggs and J2 per 100 g soil). This differentiation hints at a preferential occurrence of greater egg and J2 counts in light and sandier soil. These results accord with previous studies in which the nematode numbers were mainly studied under greenhouse conditions or in field trials (Santo and Bolander, 1979; Todd and Pearson, 1988; Francl, 1993). Nevertheless, the results suggest that the EC_a data would not enable the calculation of within-field variation on the number of eggs and J2 of *H. schachtii* to be calculated directly.

The number of eggs and J2 is assumed to be a rather variable parameter that is affected by a variety of soil properties and other environmental conditions (Wallace, 1956, 1959; Griffin 1981b; Francl, 1993). The variability of eggs and J2 at a given position within the field is affected by several biotic and abiotic factors such as soil moisture, nutrient status, weather conditions or host plant vitality. A high degree of spatial heterogeneity within the field will lead to a greater and highly dynamic differentiation of eggs and J2 over time due to variable conditions for the BCN growth. Consequently, it is assumed that more reliable results might be obtained by comparing the number of cysts per unit of soil and EC_a. Cysts remain in soil for longer periods of time and thus reflect and integrate the average living conditions over several years (Cooke, 1987). In the light of this, a rather stable property such as EC_a might become more relevant.

3.2.2 Relation between EC_a and the number of cysts

At Elmpt and Altendorf fields, both of which have a quite homogeneous texture, there was no significant correlation between the number of cysts of *H. schachtii* per 100 g soil and the EC_a data (data not shown). In contrast, there was a correlation between these properties at Billig and Palmersheim, both of which have a heterogeneous texture. At Billig field, there is a strong linear negative relation between the EC_a values and the number of cysts (R^2 = 0.74, Fig. IV.3).

At Palmersheim field, the relation is also negative, but in this case it is non-linear (Fig. IV.4). For EC_a values > 18 mS m^{-1}, the number of cysts is more or less constant, whereas below 18 mS m^{-1} the cyst count increases exponentially. The distribution of the observations can be fitted with an exponential function, which indicates a moderate

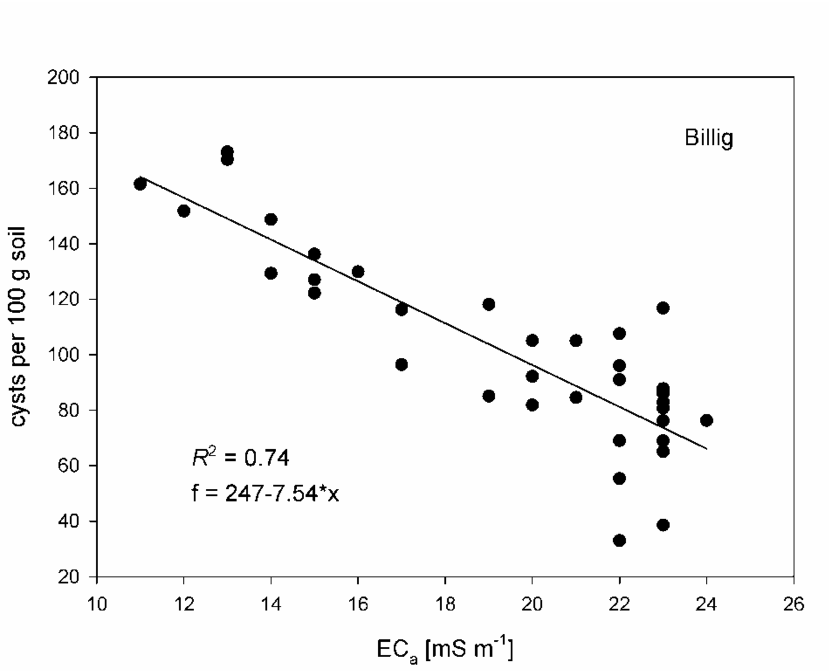

Fig. IV.3: Relationship between the EC_a values (mS m^{-1}) and the cysts of *H. schachtii* per 100 g soil at Billig field (n = 40).

relation (R^2 = 0.47). In Figure IV.4, the data points are allocated to the soil types in different parts of the field. At EC_a values < 18 mS m^{-1}, the Stagnic Luvisol with medium texture prevail. With regard to the number of cysts, the medium textured variant of the Haplic Stagnosol forms a transition between the deep Stagnic Luvisol and very large cyst counts, whereas the Haplic Stagnosol sites with heavy texture have smaller cyst counts. In the Stagnosols, stagnic properties such as water logging and pore water low in oxygen are more pronounced than in the Luvisol.

Field studies with a non-invasive soil sensor to determine the spatial distribution of the population densities of *H. schachtii* in relation to soil texture are not yet available. The results reveal that EC_a has the potential to indicate the level of BCN cysts within arable fields as long as they have a spatially heterogeneous texture. The smaller are the EC_a values, indicating a light to medium textured soil, the greater is the cyst density of *H. schachtii*. Several studies dealing with soil texture and plant parasitic nematodes evinced similar results (e.g. Todd and Pearson, 1988; Avendaño et al. 2003, 2004). In these studies the authors observed consistently greater cyst population densities of the soybean cyst nematode *H. glycines* in sandy soil. Todd and Pearson (1988) worked

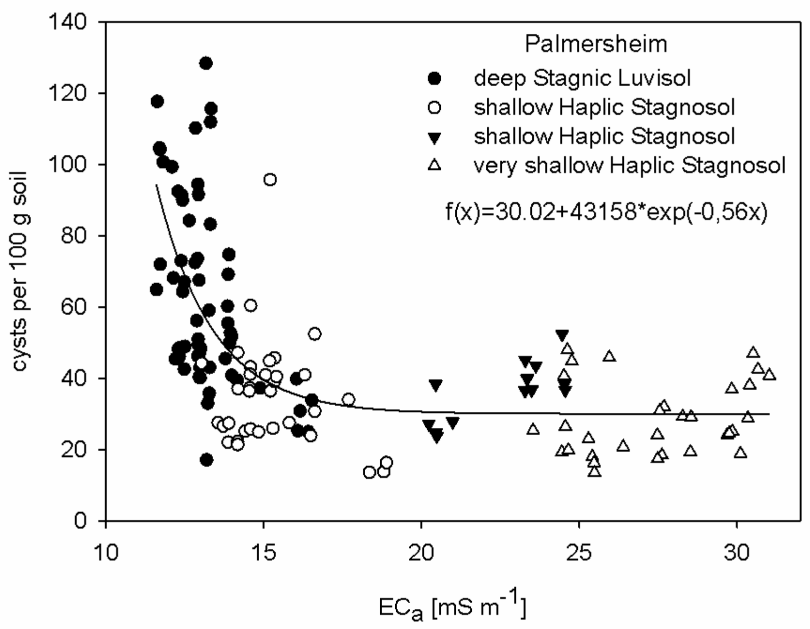

Fig. IV.4: Relationship between the EC_a values (mS m^{-1}) and the cysts of *H. schachtii* per 100 g soil at Palmersheim field (n = 140). Soil types (according to WRB) at the sampling points are marked differently.

under greenhouse conditions, whereas Avendaño et al. (2003, 2004) focussed on the spatial distribution of the nematodes within fields using geostatistics.

The highly dynamic interrelations between soil properties and nematode populations became clearly visible at both heterogeneous fields, Billig (Fig. IV.3) and Palmersheim (Fig. IV.4). The greatest cyst densities were observed at deeper and light to medium textured soils within both fields, which provide favourable environmental conditions for the development of *H. schachtii*, such as adequate pore size, soil moisture conditions at field capacity and rapid warming of the soil in the spring. In contrast, the soil hydrological dynamics in Stagnosols with temporal alternation of water logging, i.e. anaerobic conditions with oxygen deficiency on the one hand and drought stress on the other hand, is a limiting factor for nematode development. Soil aeration and the thickness of the water films are both affected by soil moisture, in which water saturation or drought soil conditions are inappropriate environmental conditions for *H. schachtii* (Wallace, 1956, 1959). In addition, water and nutrient uptake, and thus growth of the host plant, are limited by shallow and dense soil in parts of Palmersheim field. These conditions restrict root growth and thus available feeding-sites for nematodes.

Differences in soil texture are more evident at Palmersheim field and so too are the differences in the number of *H. schachtii* cysts. However, the empirically chosen exponential model for the Palmersheim data does not describe the relationship between EC_a and number of cysts per 100 g soil as well as at Billig (Palmersheim: R^2 = 0.47; Billig: R^2 = 0.74). As reported by Mertens et al. (2008) and Kühn et al. (2009a), the effects of soil horizons and related soil water dynamics can obscure pure texture effects on the EC_a values, which seems to have happened at the stagnic parts of Palmersheim field. Large EC_a values reflect the presence of a clayey layer in the subsoil, leading to a shallow rooting zone and to temporal water logging (stagnic conditions).

The results reveal that for heterogeneous fields the relations between soil texture and, if present, stagnic properties measured by EC_a and *H. schachtii* population densities can be successfully observed. Measuring EC_a is a fast and convenient method to detect the spatial heterogeneity of soil and thus a useful tool for developing management maps for nematode management.

3.3 Spatial distribution of *Heterodera schachtii* and the potential for creating management maps

The components of variance estimated by residual maximum likelihood from the nested data of Palmersheim field were accumulated and plotted against distance on a logarithmic scale to give an approximation to the variogram (Fig. IV.5). This graph shows that the residual variance at the shortest sampling distance is a small proportion of the total variance; it indicates that this sampling interval has resolved the small scale variation reasonable well. The largest proportion of variation occurs over distances between 16.7 and 30 m.

The experimental variogram of geostatistics (symbols) computed from the number of cysts of *H. schachtii* at Palmersheim field was fitted by an exponential model (solid line, Fig. IV.5). The model parameters are given on the figure. The nugget variance,

c_0, is similar to that of the residual variance of the nested analysis; this variance includes the variation that occurs over distances shorter than the smallest sampling interval and also measurement error. The spatially dependent component, c, describes the structured variation and it indicates that the sampling intervals of the nested scheme have resolved the variation in cyst density well. The exponential function reaches an upper bound asymptotically and an approximate range of spatial variation is obtained from the distance parameter of the model, r, as $3r$ (Webster and Oliver, 2007). The approximate range of spatial dependence is about 21 m (Fig. IV.5), which confirms the results from the nested analysis. This indicates that the number of cysts within the distance is spatially dependent or correlated. Samples separated by > 21 m in this field are spatially uncorrelated.

The standard sampling density for BCN detection is 5 m (Müller, 1983), and for this field it would provide spatially correlated data that would be suitable for interpolation by kriging or any other method. However, the spatial scale from the nested survey and variogram analysis of BCN in this field suggests that some economy in sampling

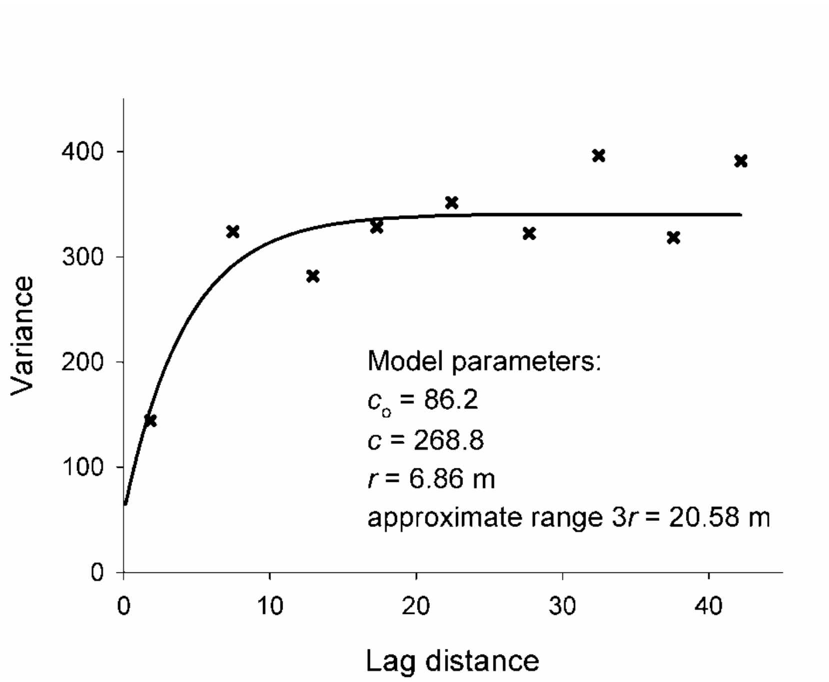

Fig. IV.5: Experimental variogram (symbols) and fitted exponential model (solid line) for *H. schachtii* cyst density at Palmersheim field.

density would be feasible with an interval of 10 m. Nevertheless, for heterogeneous variables such as cyst nematodes additional samples at shorter distances are recommended to ensure that the spatial variation is resolved adequately.

Other research on nematode density has resulted in variogram ranges of between 12 and 60 m (Webster and Boag, 1992; Evans et al., 2002; Avendaño et al., 2003; Dinardo-Miranda and Fracasso, 2009). These diverse results illustrate the difficulties of suggesting a definite sampling density for site-specific management of nematodes. Webster and Boag (1992) and Evans et al. (2002) stated that spatial patterns of nematodes are unique in each field and that there is no common range of spatial dependence or sampling interval. However, as a result of the cost and time taken to survey fields infested with *H. schachtii*, it is not feasible to obtain sufficient data for variogram analysis of each field. Management maps including management zones based on EC_a data should provide a basis to target sampling for BCN.

For heterogeneous sugar beet fields with a known BCN infestation, information on the spatial distribution of the risk of damage from BCN may be useful not only for sampling, but also for future cropping strategies and measures. Thus, the possibility of deriving management maps based on EC_a data and on additional information from soil taxation maps was tested for the heterogeneous fields, Billig (Fig. IV.6) and Palmersheim (Fig. IV.7). These maps were compared with spatial patterns of nematode population densities. At Billig, the smallest EC_a values are in the south-west corner and they gradually increase towards the north-east and decrease again in the north. The EC_a values of the western central area have a patchy distribution with small, medium and large EC_a values. Based on information from the soil taxation map, the smallest EC_a values indicate deep soil with a rather low soil quality index (①: 48 – 54) and the largest EC_a values indicate shallow soil with a higher soil quality index (②: 68; Fig. IV.6). The results of the own soil surveys compare with the spatial distribution of EC_a and soil quality index described above, indicating medium (①) and more heavy (②) textured soils at Billig field. Figure IV.6 also illustrates that the number of cysts of *H. schachtii* is closely related to the values of EC_a: *H. schachtii* prefers the deeper, light textured soil in the south-western part of the field where EC_a values are small and cyst counts are large.

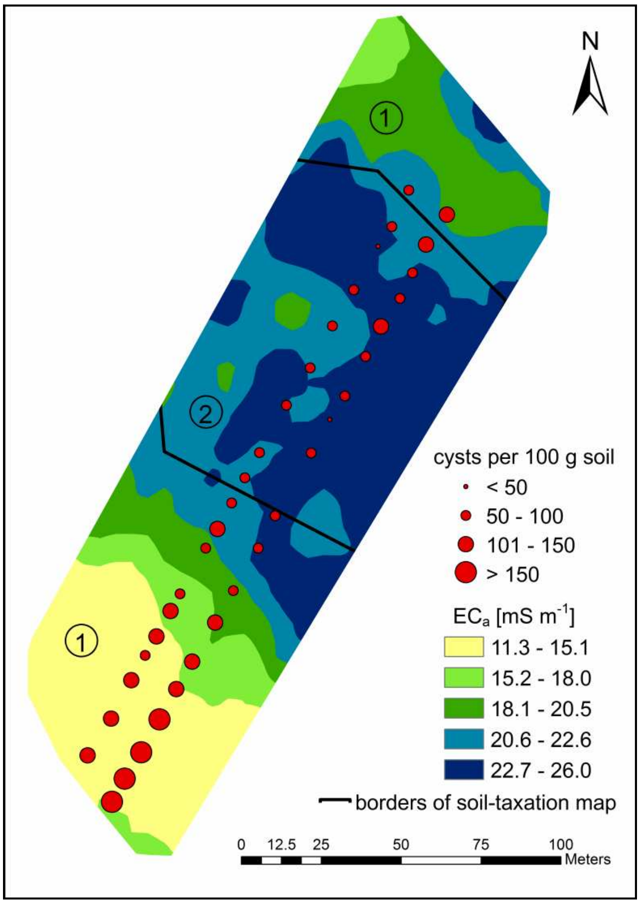

Fig. IV.6: EC_a map including information from a soil taxation map (① deep Haplic Cambisol, soil quality index = 48 – 54; ② shallow Haplic Cambisol, soil quality index = 68) and related numbers of *H. schachtii* cysts per 100 g soil at Billig field (n = 40).

Palmersheim field is characterised by a trend in EC_a values with small values in the north-western part and the largest values in the south-east. This distribution again relates to the boundaries of the soil taxation map (Fig. IV.7a). The smallest EC_a values correspond to a deep (①) Stagnic Luvisol and partly shallow (②) Haplic Stagnosol with a soil quality index of 56 – 62 in the northern part of the field, whereas the largest EC_a values correspond to a shallow (③) and very shallow (④) Haplic Stagnosol with a soil quality index of 42 – 44 and clayey subsoil in the southern part of the field. The spatial distribution of cysts of *H. schachtii* confirms the relation between soil texture with large cyst numbers in the north-west and small numbers in the south-east. It also confirms that BCN prefer deep, medium textured soils and non-stagnic conditions (Fig. IV.7b).

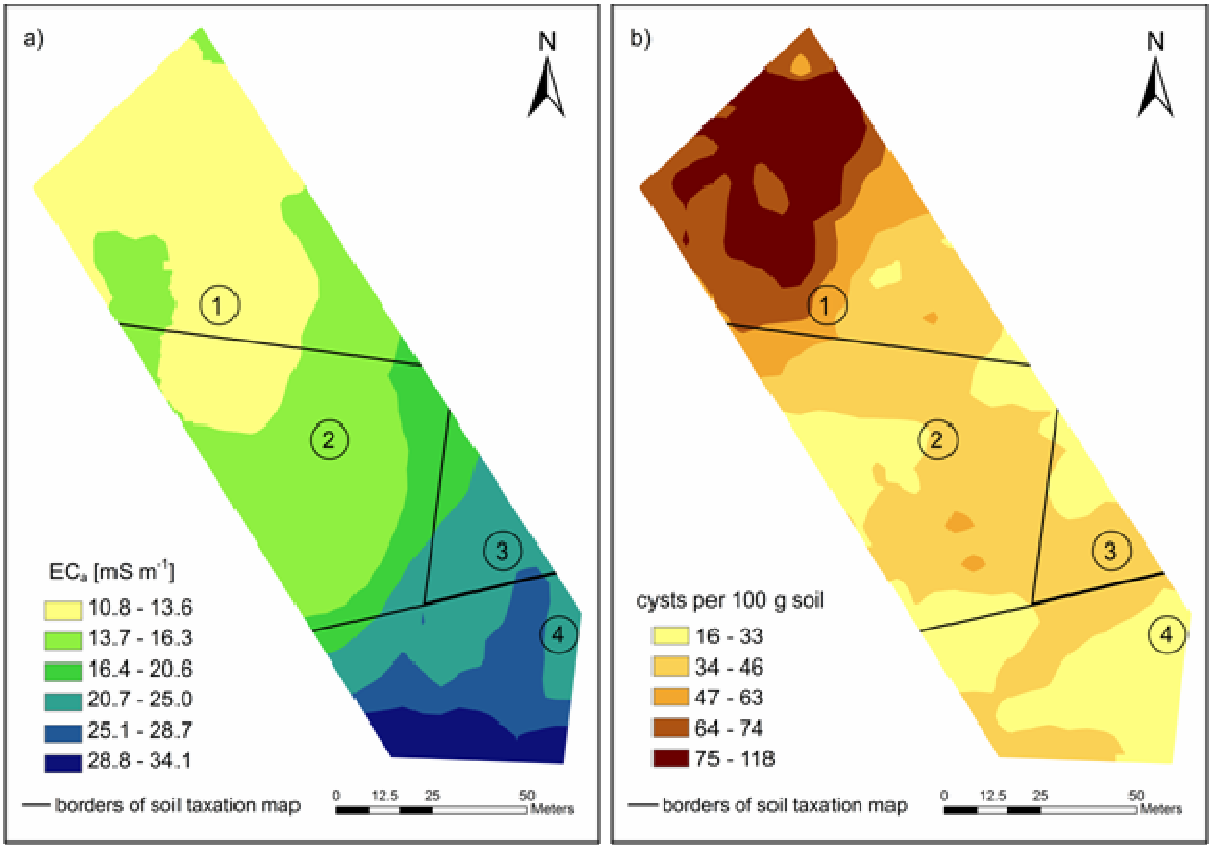

Fig. IV.7: Palmersheim field: a) EC_a map including information from a soil taxation map (① deep Stagnic Luvisol, soil quality index = 62; ② shallow Haplic Stagnosol, soil quality index = 56; ③ shallow Haplic Stagnosol, soil quality index = 44; ④ very shallow Haplic Stagnosol; soil quality index = 42) in comparison with b) nematode population densities of *H. schachtii* in terms of cysts per 100 g soil (n = 140).

The combination of soil taxation and EC_a maps is reasonable because of the lack of depth information from the EM38 signal. Without local calibration, i.e. without additional information from soil cores or from soil maps, the EC_a values cannot be used reliably to derive soil properties beyond depth-averaged texture. However, when such additional information from soil taxation or other soil maps is available, then soil horizons can be detected and can explain the reason for stagnic properties (e. g., Mertens et al., 2008). Nevertheless, soil maps seldom indicate gradual variation, but show sharp boundaries, and although they are available the scale does not enable subplot-specific interpretation. Therefore, the EC_a measurements often provide the only possibility of obtaining high-resolution soil information at reasonable effort and costs. Furthermore, the combination of the vertical and the horizontal dipole mode of the EM38 can provide further insight into deeper soil layers (Sudduth et al., 2001), but this was not part of this study.

The results show that if an arable field with textural heterogeneity is infested with *H. schachtii*, EC_a measurements can be used to create management maps (Fig. IV.8). Based on information from these management maps, an agricultural field can be separated into different zones that can be used for management. The management zones in Figure IV.8a reflect EC_a values, which, in turn, reflect the soil taxation map at Billig field. In parallel, the zones correspond with the spatial distribution of BCN (Fig. IV.6). The same relations are evident at Palmersheim field, when Figure IV.8b is compared with Figure IV.7b. Dicke et al. (2007) and Patzold et al. (2008) discussed

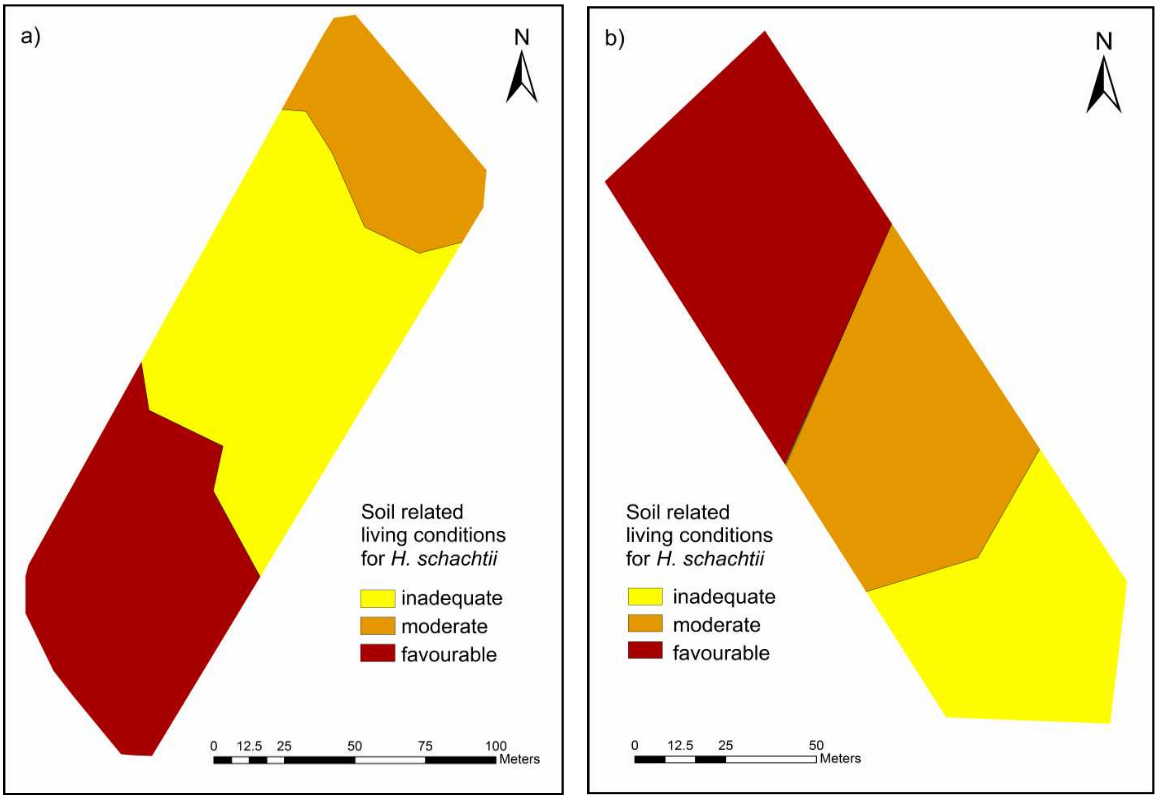

Fig. IV.8: Management maps established on the basis of EC_a maps including information from soil taxation maps showing soil related living conditions for *H. schachtii* and thus management zones at a) Billig field and b) Palmersheim field. Management zones are relative graduations within each field.

the creation of management zones for crop protection purposes. Site-specific management strategies concerning the distribution of BCN can be oriented to a threshold of the observed damage. Cultivars that are tolerant or resistant to *H. schachtii* are required by farmers if the use of nematicides is not authorised, even if resistant cultivars often have smaller yields, are of poorer quality and cost more compared to tolerant or susceptible species (Heinicke and Warnecke, 2006). However, site-specific management decisions such as sowing of cultivars with different degrees of susceptibility at the field scale can be made before the growing season starts. This is a clear advantage of management maps based on EC_a data and information on soil texture compared with other methods that are used for the detection of variable nematode densities within fields, such as hyperspectral data imaging (Hillnhütter et al., 2011b). Furthermore, individual parts of a field can be sampled separately to determine the population density of *H. schachtii* and so reduce the overall number of samples required.

An interpolated management map based on geostatistical analysis is required by agronomists and farmers to manage land in a reasonable and site-specific way (Oliver and Webster, 1991). The results reveal a convenient way for producing maps of nematode management zones. The close relationship between soil texture and EC_a and its effect on nematode population density offers new approaches for site-specific nematode management. The viability and feasibility of this method for other crops and plant parasitic nematodes needs to be investigated. Mueller et al. (2010) recently developed a site-specific nematicide application system. It is based on studies in the USA on the root-knot nematode *Meloidogyne incognita* in cotton to minimise nematode damage while reducing nematicide contamination of the environment. They created accurate and effective maps of nematode management zones based on the EC_a values combined with elevation, slope and vegetation indices from leaf reflectance. Avendaño et al. (2004) also mentioned that soil survey maps can serve as useful tools to predict *H. glycines* in infested fields. They suggested a comparison between soil texture and areas with expected high cyst density. Hence, their findings and hypothesis are in line with the presented results, even though they did not create management maps and were dealing with different cyst nematode species. Management maps based on the EC_a values that indicate soil textural zones in heterogeneous fields are appropriate for site-specific management of *H. schachtii*-infested sugar beet fields.

4 CONCLUSIONS AND PERSPECTIVES

The results indicate that arable fields that are infested with *H. schachtii* and heterogeneous in texture reveal a strong to moderate relationship between spatial patterns of *H. schachtii* cysts and EC_a. Based on this observation, the EC_a can be used to create management maps. Additional information from high-resolution soil maps helps to refine the interpretation of EC_a values. The EC_a-based management maps enable farmers to decide on suitable site-specific management strategies for nematode-infested fields and to realise ecological and economic benefits. Also soil sampling and nematode counting can be modulated in a site-specific way. The procedure described could also be transferred to other crops and plant parasitic nematodes such as *Ditylenchus dipsaci* on sugar beet or *Pratylenchus penetrans* on maize, and as well on plant pathogens such as *Rhizoctonia solani*, if a relationship to soil texture is proved. A combination of innovative techniques (EC_a measurements, hyperspectral data imaging) should be taken into consideration in future studies. Nevertheless, further investigations should also focus on the optimisation of sampling strategies and densities. Therefore, more fields need to be investigated for a better understanding of the spatial interrelations between nematodes and soil properties.

The spatial patterns of *H. schachtii* at the field scale have not been investigated before using soil heterogeneity evaluated by EC_a. The results indicate the possibilities and limitations of non-invasive sensor technologies to improve management strategies for plant parasitic nematodes. Under given circumstances (BCN infestation, heterogeneous soil texture), management zones can be implemented with existing knowledge. It is recommended that the results and the new approaches from this research find their way into applied precision agriculture.

V

Spatiotemporal weed dynamics as affected by soil properties – a case study

1 INTRODUCTION

Weeds compete with crops for water, nutrients and light and, thus, cause severe yield losses at arable fields across the world (Marshall et al., 2003). Site-specific species compositions and weed patches with different plant densities often occur within arable fields, depending on many environmental and human-induced factors (Rew and Cousens, 2001). According to Gerhards and Christensen (2003), further investigations about temporal and spatial stability of weed patches and the effect of soil properties is necessitate for site-specific weed management. Maps including management zones could be built on the basis of soil maps to improve weed density and distribution estimates (Rew et al., 2001; Walter et al., 2002). Furthermore, long-term data sets are required for high prediction accuracy (Rew and Cousens, 2001). Within this study, spatial weed species distribution and density (weed variability) in relation to soil properties was observed within a long-term survey over nine years on one arable field. Using non- and minimal-invasive sensor technologies, site-specific weed management ought to be improved and weed management maps on the basis of soil maps ought to be created.

2 MATERIAL AND METHODS

2.1 Test field

The long-term weed survey was conducted on an arable field with a subplot of 5.8 ha size at Dikopshof Research Station near Bonn, Germany (6°57´17´´ E, 50°48´17´´ N). The mean annual temperature is 9.7°C and the mean annual precipitation amounts to 630 mm. Grain maize, sugar beet and winter cereals (winter wheat and winter barley) built up the crop rotation on the test field. This uniform 4-years crop rotation was consistently realised with plough tillage and equalised fertilisation since several decades.

The test site is characterised by considerable soil heterogeneity. The soil developed from loess and sandy and gravelly alluvial sediments over the sandy-stony, highly permeable Pleistocene middle terrace of the river Rhine. Depending on the thickness of the loess cover (0.27 to > 1.50 m), the parent material consists of unweathered loess or Pleistocene terrace sediments. Thus, soil texture and porosity vary in a wide range. Soil types alternate, according to the WRB (FAO, 2006), between Haplic Cambisols, Luvic Cambisols, Haplic Luvisols and Colluvic Regosols.

2.2 Experimental design for weed determination

Weed seedlings were determined every year in spring prior to herbicide application from 1998 – 2008 with an interruption in 2004 and 2005. Site-specific weed control was conducted within an experiment regarding the spatial dynamics of *Chenopodium album* (L.) from 1997 – 2003 on the test field (Dicke et al., 2007). The same regular grid (15 × 7.5 m) was established in the test field throughout the study years. Weed seedlings were counted in a 0.4 m^2 frame placed at all intersection points (n = 429, Fig. V.1a). The number of individual weed species was multiplied with the factor 2.5 to get the number of plants m^{-2}. While broadleaved weeds (dicots) were separated in each occurring species, varying species of grass weeds (monocots) were summarised, because the grass weeds were clearly dominated by *Alopecurus myosuroides* (Huds.).

2.3 Soil sampling and analyses

Soil samples were taken from 0 to 30 cm depth (plough horizon) with an auger at the end of the long-term survey at the intersection points of the weed grid. The spatial coordinates were recorded using differential GPS. Due to the high number of samples (n = 429), just a part of them (n = 127) was analysed with conventional laboratory methods. In addition, all soil samples were air-dried, sieved (< 2 mm) and milled for further evaluation using MIRS-PLSR (see section II.1 and II.2). If this technique did not reveal satisfying results, the tool ‘Buffer’ in ArcGIS Editor 9.3 was performed to evaluate the non-measured samples. Averaged values within the buffer zones were readout to calculate the missing values using the option ‘Zonal Statistics’ within the additive tool ‘Hawth Tools’.

2.3.1 Physical soil properties

Soil texture was determined by a combination of wet sieving (sand fractions) and sedimentation (silt and clay fraction) after Köhn (ISO 11277, 2002). Additionally, the apparent electrical conductivity (EC_a) was measured directly in the field with the non-invasive EM38 sensor (see section II.3). Two geological layers (loess, sandy and gravelly alluvial sediments) at the test site markedly differed in soil texture and thus affected EC_a values. Mertens et al (2008), who observed the same test field as in this study, suggested that EC_a data can be used to predict further soil properties via pedotransfer functions. Due to the geological situation (homogeneous loess of varying thickness over sand and gravel) and the related physical soil properties of the test field under study, the calculation of the available water capacity (AWC) from EC_a values was possible. Thus, in this special case, AWC in mm was calculated for 1.5 m soil depth (i.e., the main root zone) on the basis of the EC_a data with supplementary local calibrations. The AWC can be considered as an indicator for the duration of water supply to crops and weeds during dry periods.

2.3.2 Chemical soil properties

Total carbon and nitrogen (C_t, N_t) were analysed after dry combustion with an elemental analyser (Fisons NA 2000; ISO 10694, 1995). The plough horizon of the entire field is free of carbonate; in consequence, C_t corresponds to SOC. Particulate organic matter (POM) was fractionated by ultrasonic dispersion and sieving, separating coarse (POM1, 2000 – 250 µm), intermediate (POM2, 250 – 53 µm) and fine (POM3, 53 – 20 µm) fractions (Amelung and Zech, 1999; Kölbl et al., 2005). Plant available P and K were determined using calcium-acetate-lactate (CAL) extraction, while Mg was extracted with 0.01 M $CaCl_2$ solution. Soil pH was measured potentiometrically in a 0.01 M $CaCl_2$ suspension.

2.4 Data analyses

Multidimensional data such as population or environmental properties can be successfully analysed using multivariate ordination techniques (Lepš and Šmilauer, 2003). While this method is widespread in plant research (Hejcman et al., 2010; Šrek et al., 2010) it can also be adapted to weed science (Pinke et al., 2009, Hyvönen et al., 2010). Redundancy analysis (RDA) was performed with the CANOCO 4.5 program (ter Braak and Šmilauer, 2002) to evaluate the effect of various and interfering physical and chemical soil properties and other environmental parameters on the spatial variation of weed species density. A pre-test in the form of a detrended correspondence analysis (DCA, with detrending by segments) was used to decide about the right ordination method according to the data set. Hence, RDA was the method of choice because the length of the gradient in DCA was 1.4. Furthermore, the environmental variables were in the form of categorical predictors (cf. Lepš and Šmilauer, 2003). Data were logarithmically transformed due to positively skewed distribution and large standard deviations. Possible significant effects of the explanatory variables (environmental variables in the CANOCO terminology) on the weed species were tested using a Monte Carlo test with 999 permutations. Bi-plot ordination diagrams were created with CanoDraw software to visualise the results of the multivariate analysis. The percentage of the weed species data variability explained by soil properties or other environmental parameters was used as a measure of explanatory power.

The RDA examines how a set of explanatory variables (environmental variables such as years, field crops and soil properties in this study) affect another set of variables (weed data variability). According to Lepš and Šmilauer (2003), the relative importance of the canonical axes decreases from the first up to the last canonical axis. Therefore, they suggest that the focus within the results and the displayed ordination diagram should be on the first canonical axis, which implies most of the explanatory power to express data variability. The statistical evaluation of the performed Monte Carlo Permutation test is given with the F- and P-values for the first canonical axis and for all canonical axes in this study. The highest statistical significance is given with a P-value of 0.001 with 999 permutation tests. The F- and P-values of the Monte Carlo Permutation test can be used with analogous meanings as in ANOVA regression analysis. Further details are given by Lepš and Šmilauer (2003).

The spatial heterogeneity of weed patches for all years under study were analysed with the exploratory tool ‘Geographically Weigthed Regression’ (GWR) in ArcGIS Editor 9.3 following the instructions by Charlton and Fotheringham (2009). GWR is a type of local statistics that includes the weighting of all observations around a sampling point, whereas observations closer to the sampling point have higher effects on the calibration model (Tu and Xia, 2008; Perry et al., 2010). The weighting function depends on a kernel bandwidth. A fixed kernel was used for the weed data, because the sampling points were regularly positioned within a grid. The bandwidth with the best prediction accuracy was determined with the corrected Akaike Information Criterion (AICc). GWR models generate a local linear regression including statistical parameters, such as the coefficient of determination, R^2.

Global Moran´s I was calculated for the residuals of the GWR models. Moran´s I is an index to describe the spatial autocorrelation of data and thus the stability of weed patches for all years under study (Tu and Xia, 2008; Perry et al., 2010). In general, a Moran´s I value near +1.0 indicates clustering, whereas a value near -1.0 indicates dispersion. *Z*- and *p*-values provide statistical significance. Large Z values (> 1.96) reject the assumed null hypothesis and p values < 0.05 indicate statistical significance when using a 95% confidence level.

Univariate analyses were performed via IBM SPSS statistics 19 software (IBM Corporation 2010, New York, USA). One-way ANOVA followed by post-hoc comparison using Tukey´s test was applied to identify significant effects of various field crops on the distribution of weed species.

2.5 Geostatistical data processing

Geostatistical data processing and the creation of maps were performed as described in section II.4.

3 RESULTS AND DISCUSSION

3.1 Variability of weed distribution within the long-term survey

The weed distribution in the test field revealed a considerable spatial heterogeneity concerning the local patterns of the different species as well as their density. Dominant weed species were *C. album*, *Polygonum aviculare* (L.), *Viola arvensis* (Murray) and grass weeds, the latter dominated with about 80% by *A. myosuroides* (Fig. V.1). Hence, these four species were chosen for data analyses due to their frequently and consistent occurrence. All weed species revealed a positively skewed distribution in each year of observation. On average, the highest weed density within the whole study period was observed for *V. arvensis* with 14 plants m^{-2}, while the mean weed density of the other three species was about 11 plants m^{-2} (Fig. V.1). Weed patches with a density up to about 280 plants m^{-2} were found in single years for each species except for *C. album* with a maximum weed density of 155 plants m^{-2}.

The dominance of the weed species varied between the years, but the spatial patterns remained stable for observations over one decade, as evaluated by GWR and Global Moran´s I (Tab. V.1). The high coefficients of determination (R^2 = 0.96 – 0.98) indicate a high spatial heterogeneity of weed patches. Significant positive autocorrelations (p < 0.001) were found for all observed GWR models of the four weed species. Positive Moran´s I values (0.11 – 0.22) and large positive Z values (6.09 – 16.53) indicate that weed species abundance between 1998 and 2008 is spatially correlated.

Stable weed patterns over two to four years were observed at various agricultural fields (Nordmeyer and Niemann, 1992; Johnson et al., 1996; Gerhards and Christensen, 2003; Mehrtens, 2005). Dicke et al. (2007) observed stable spatial patterns of *C. album* from 1997 – 2003 on the same test field without significant effects of site-specific herbicide application, which can be explained by the limited period of time in their study. Weed species abundance is, amongst others, affected by the current field crop. Thus, it is possible that effects of site-specific weed control on weed species variability become primary visible if several cycles of crop rotation are observed. However, this was not the focus of the present study.

Tab. V.1: Coefficient of determination (R^2) of results from Geographically Weighted Regression (GWR) of weed species abundance between various years within the long-term survey and Global Moran´s I of the residuals from GWR models

Statistical test results	*Chenopodium album*	*Polygonum aviculare*	*Viola arvensis*	grass weeds
R^2	0.98	0.98	0.97	0.96
Moran´s I	0.12	0.11	0.22	0.15
Z	6.70	6.09	16.53	11.06
p	< 0.001	< 0.001	< 0.001	< 0.001

Long-term surveys over one decade regarding spatial weed patterns as conducted in this study are not known yet. Site-specific preferences of the individual species at the test site are displayed as the mean abundance of the whole study period in Figures V.1c – f. Obviously, *C. album* and *V. arvensis* prefer opposed site conditions (Fig. V.1c, e). The highest densities of *C. album* were observed in the north of the test field, while the highest densities of *V. arvensis* were found in the southern part. The opposite gradients of both weed species do not depend on different field crops or tillage systems as it looks like, but are partially correlated with the AWC (Fig. V.1b). *P. aviculare* and grass weeds evidently revealed opposite gradients, but with clear similar patterns as the AWC (Fig. V.1b, d, f). While *P. aviculare* seems to prefer areas with low to medium AWC (< 140 mm), grass weeds favour sites with extremely high AWC (> 250 mm). A visual comparison between weed species distribution and AWC map suggest a certain relation between spatial weed distribution and AWC. Furthermore, the spatial variation of AWC obviously coincides with spatial patterns of the aerial image from August 1998, showing differences in biomass of grain maize (Fig. V.1a, b). Timmermann et al. (2003) and Mertens et al. (2008) studied the same test field. Both found a similar pattern between soil fertility (soil texture and related water holding capacity) and growth of maize and grain yield, respectively. Hence, the soil water supply affects the competitiveness of weeds and crops.

3.2 Physical and chemical soil properties

Soil texture, N_t and SOC could be predicted with high accuracy via MIRS-PLSR. The coefficient of determination (R^2 = 0.92 – 0.99) as well as RMSECV (2.30 to 17.50 g kg^{-1} for texture parameters and 0.21 g kg^{-1} for SOC), the RPD (3.53 to 8.31) and the RMSEP for 30% test-set validation (2.70 to 21.10 g kg^{-1} for texture parameters and 0.20 g kg^{-1} for SOC) corroborate the excellent quality of the calibration models (Tab. V.2).

The spatial distribution of the investigated soil properties was heterogeneous within the test field; Table V.3 presents related statistical parameters. While soil texture in the

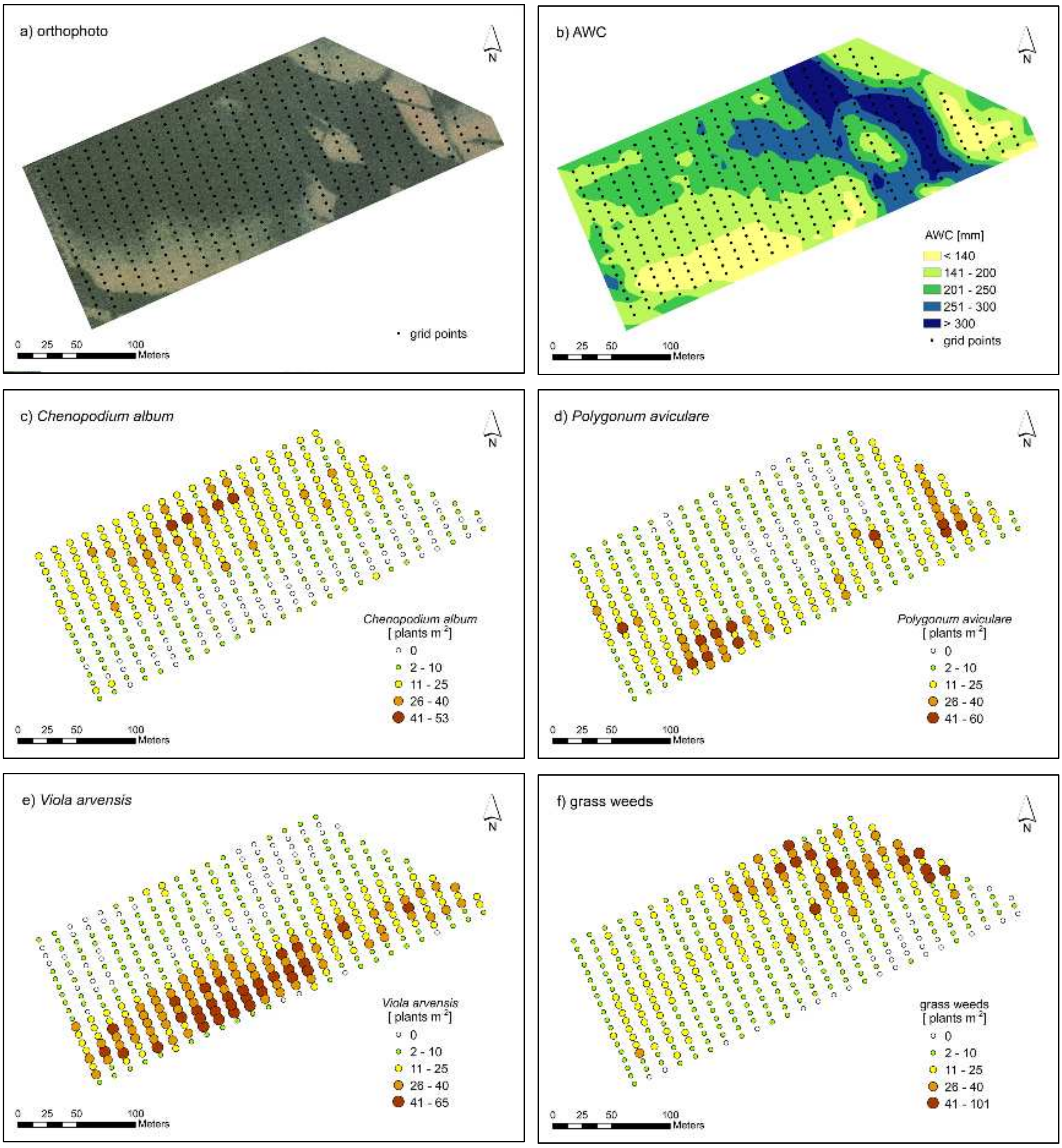

Fig. V.1: Spatial patterns in the test field: a) Aerial image (orthophoto) from August 2008 including intersection points of the sampling grid; crop: maize; b) available water capacity (AWC) including intersection points of the sampling grid; mean abundance (plants m^{-2}) of the whole study period (1998 – 2008) for c) *Chenopodium album*, d) *Polygonum aviculare*, e) *Viola arvensis* and f) grass weeds.

Tab. V.2: Statistical parameters of mid-infrared spectroscopy-partial least squares regression (MIRS-PLSR). Predictions were conducted for mean contents of clay, silt, sand, soil organic carbon (SOC) and total nitrogen (N_t) in the topsoil

Soil constituent	Full cross-validation			Test-set validation (30%)		
	R^2	RMSECV[a]	RPD[b]	R^2	RMSEP[c]	RPD[b]
clay (g kg^{-1})	0.98	2.30	6.64	0.97	2.70	5.65
silt (g kg^{-1})	0.94	17.50	3.99	0.93	21.10	3.81
sand (g kg^{-1})	0.99	9.51	8.31	0.98	11.50	7.25
N_t (g kg^{-1})	0.79	0.04	2.18	0.78	0.04	2.14
SOC (g kg^{-1})	0.92	0.21	3.53	0.93	0.20	3.66

[a] Root mean square error of cross validation.
[b] Ratio of performance to deviation.
[c] Root mean square error of prediction.

plough horizon was relatively stable, AWC of 1.5 m soil depth ranged from 57 to 426 mm, indicating a considerable variation due to the geological situation of the field (cf. 2.1, 2.3.1). It should be noted that AWC was calculated to a depth of 1.5 m, whereas soil texture was determined only in the plough horizon (0.3 m). Due to the spatially changing of the pronounced layering of the test field soil, the AWC as determined via EM38 measurements is only little affected by soil texture conditions in the uppermost 0.3 m, but dominated by the texture in soil horizons to 1.5 m depth. Mertens et al. (2008) observed a strong positive correlation between EC_a and clay content and a strong negative correlation between EC_a and sand content to 1.5 m soil depth at the test field. Due to this layering and the different measurement depths, AWC as derived from EC_a for 1.5 m soil depth and soil texture in the plough horizon have to be examined separately.

N_t and SOC were closely correlated, but did not show a high spatial variation within the test field. The spatial patterns of the different fractions of POM1, POM2 and POM3 as well as of soil pH were rather homogeneous, while the plant available amounts of P, K and Mg were heterogeneously distributed within the test field (Tab. V.3). Ritter et al. (2008) discussed the variability in weed distribution, soil quality and herbicide application as affecting grain yield. These parameters should be taken into consideration for site-specific weed management decisions. Thus, the further focus was on the effect of different environmental parameters on weed variability.

Tab. V.3: Statistical parameters of the observed soil properties. Data refer to the plough layer except AWC

Soil properties	Min	Max	Mean	Median	SD[a]
clay (g kg^{-1})	120.1	185.9	156.1	156.6	9.2
silt (g kg^{-1})	501.4	713.5	653.2	661.7	31.0
sand (g kg^{-1})	132.6	330.6	194.0	183.3	36.5
AWC (mm)[b]	57	426	207	206	74
Nt (g kg^{-1})	0.85	1.31	1.03	1.03	0.08
SOC (g kg^{-1})	9.78	15.19	11.69	11.66	0.75
POM1 (g C kg^{-1})[c]	0.25	2.08	0.72	0.69	0.17
POM2 (g C kg^{-1})[c]	0.24	1.25	0.54	0.52	0.12
POM3 (g C kg^{-1})[c]	0.71	2.25	1.26	1.25	0.16
P-CAL (mg kg^{-1})	0.47	1.29	0.74	0.74	0.10
K-CAL (mg kg^{-1})	0.79	2.52	1.15	1.16	0.19
Mg-$CaCl_2$ (mg kg^{-1})	0.13	0.62	0.47	0.48	0.11
pH-$CaCl_2$	6.36	7.22	6.82	6.84	0.12

[a] SD = standard deviation.
[b] AWC = available water capacity, summarised about 1.5 m soil depth.
[c] POM = particulate organic matter of the coarse (POM1, 2000-250 µm), intermediate (POM2, 250-53 µm) and fine (POM3, 53-20 µm) fraction.

3.3 Variability of weed distribution as affected by environmental parameters

The density of the individual weed species clearly differs between field crops. The dynamic relations of weed species at the test site within and between individual field crops are displayed in Figure V.2. All weed species revealed significantly highest densities in the summer annual row crops (grain maize and sugar beet), with the exception of *V. arvensis*, whose density does not differ between sugar beet and winter cereals. Weed populations in grain maize were significantly dominated by *C. album*, while grass weeds significantly dominated weed species composition in sugar beet. In winter cereals, *V. arvensis* was the most frequent species (Fig. V.2).

Gardarin et al. (2010) stated that *C. album* and *P. aviculare* only emerge in spring and also Roberts and Potter (1980) observed the highest number of *P. aviculare* seedlings after cultivation in spring. Cousens and Mortimer (1995) described the effect of winter and summer crops on weed emergence, whereat in general weeds develop more poorly in winter crops due to a general germination of many weeds in spring into an established crop canopy. As a thermophile weed, *C. album* needs high germination

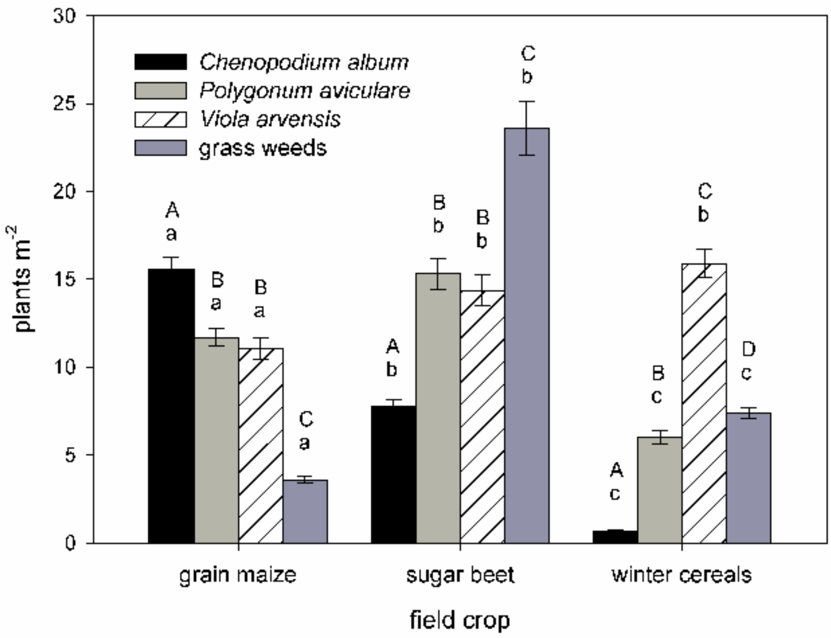

Fig. V.2: Averaged weed density of individual species in relation to varying field crops. Different small letters indicate significant differences ($p < 0.05$) of individual weed species between field crops; different capital letters indicate significant differences ($p < 0.05$) between weed species within individual field crops. Bars indicate standard error.

temperatures and thus prefers summer annual field crops (Mehrtens, 2005). Also Andreasen et al. (1991) observed a higher abundance of *C. album* in summer annual crops than in winter annual crops. *V. arvensis* and *A. myosuroides* are characteristic weeds in winter cereals (Gerhards et al., 1997). It can be concluded that the presented findings of high *C. album* and *P. aviculare* abundance in summer annual row crops and high *V. arvensis* abundance in winter cereals are in line with reports from literature.

During the long-term survey, significant differences in weed density were also found between particular years (data not shown). Such year-depended differences in weed density and composition can be caused by many parameters. Beside field crop rotation, particularly soil tillage affects weed emergence (Cardina et al., 2002; Sosnoskie et al., 2006). This effect can be certainly regarded as negligible in the present study due to consistent plough tillage during the whole experimental period. However, climatic conditions, especially temperature and rainfall, affect weed population dynamics (Cousens and Mortimer, 1995; Kobusch, 2003). Furthermore, weed density, competition pressure and thus interrelations between weeds and crops additionally modify species composition (Cousens and Mortimer, 1995; Ritter and Gerhards, 2008). Thus, multivariate analyses (RDA) were performed for the explanatory variables years, field crops and soil properties to analyse the effect of these factors on weed variability.

According to RDA, the environmental variables had significant effects on the weed data variability (Tab. V.4). The effect of years, field crops and soil properties together explained 47% (analysis a1, all canonical axes) of variability in weed species for all years of the long-term survey separated, while the first canonical axis explained just 20.8% of weed data variability (analysis a1, ax 1). Considering all canonical axes for each explanatory variable separately, the factor years explained the highest proportion of weed species variability (36.9%, analysis a2), while various field crops revealed the lowest explanatory power (11.2%, analysis a3, Tab. V.4). For year-dependent analysis, weed data of all years of the long-term survey were separated, while for field crop-dependent analysis only weed data of the years with different field crops were separated. Averaged weed data of all years were used for soil-dependent analysis, because soil data were just collected once. The different soil properties together explained 26.4% of the variability in weed species (analysis a4). Taking the first canonical axis into account, which implies most of the explanatory power, the factor soil still explained almost one fourth (23.7%) of weed data variability, while the explanatory power of the years decreased to 18.3% (Tab. V.4).

Tab. V.4: Results and statistical evaluation of redundancy analysis (RDA) of weed species abundance for all years separated in relation to years, field crops and soil properties

No.	Explanatory Variable	First canonical axis			All canonical axis		
		%	*F*	*P*	*%*	*F*	*P*
a1	years, field crops, soil	20.8	1005.6	0.001	47.0	161.9	0.001
a2	Years	18.3	863.3	0.001	36.9	281.6	0.001
a3	field crops	9.6	410.7	0.001	11.2	243.0	0.001
a4	Soil	23.7	129.2	0.001	26.4	11.5	0.001

Interpreting year-dependent and field crop-dependent changes in weed abundance is complex due to different sowing dates and corresponding weather conditions as well as to inter- and intra-species competitions. Andreasen et al. (1991) observed varying climatic conditions during a 13-year study, which affected just 11 out of 37 weed species significantly. However, field crop- and year-dependent changes can explain some temporal variation in weed species abundance in the present data set. Neither differences of years nor the effect of different field crops can solely explain the spatial variability of weed species. Thus, the further focus was on the effect of various soil properties, which explain weed data variability with almost 25% (Tab. V.4).

3.4 Variability of weed distribution as affected by soil properties

Various soil properties were analysed to explain weed species abundance. Soil properties such as soil texture and related AWC as derived from electromagnetic measurements as well as SOC can be regarded as stable over time under consistent tillage (Paustian et al., 1997; Mertens et al., 2008). Due to consistent liming and fertilisation also soil pH and plant available nutrients are more or less stable soil properties in the long-term survey. For multivariate analyses of various soil properties averaged weed data from all studied years were used.

The first canonical axis of RDA represents the majority of weed variability among the soil properties (Tab. V.5). Hence, these percentages were considered as adequate to the explanatory power. All measured soil properties together significantly explained 34% of the variability in weed species data (analysis a5), visualised in an ordination diagram (Fig. V.3). Weed species are clustered together with affecting soil properties, while soil properties with less or no effect on weed species are more widely separated. Weed species are more or less clearly positively or negatively correlated to different texture parameters, AWC and soil pH. Large arrows of N_t and SOC indicate also a high, but more non-directional effect on weed species abundance (Fig. V.3). The available nutrients as well as the amount of POM fractions show only a weak and non-directional effect on specific weed species.

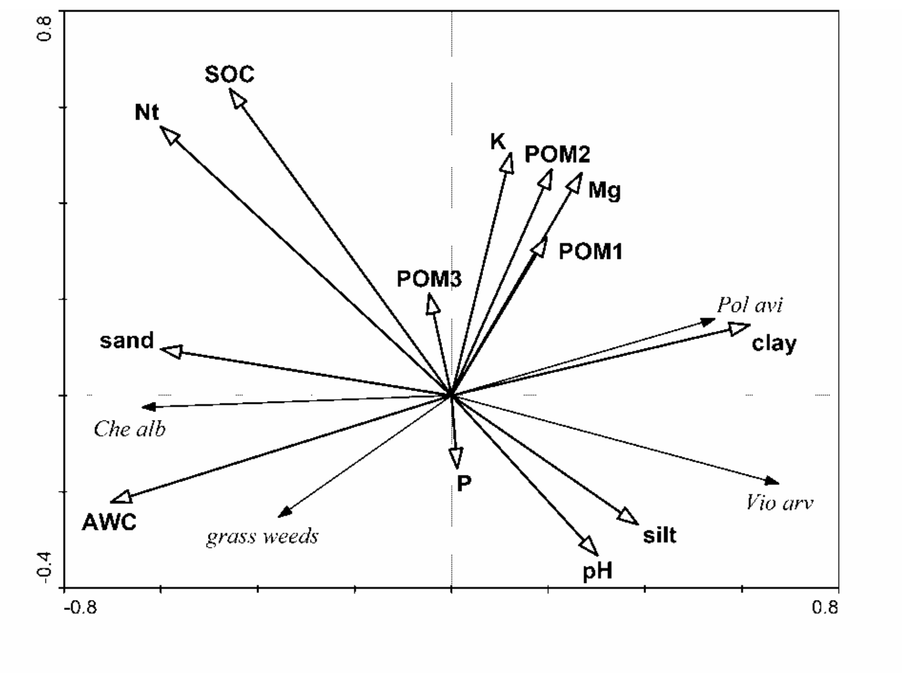

Fig. V.3: Ordination diagram visualising the results of the redundancy analysis (RDA) with all measured soil physical and chemical properties used as environmental (explanatory) variables (AWC = available water capacity; POM = particulate organic matter; SOC = soil organic carbon). Species abbreviations: *Che alb* – *Chenopodium album*, *Pol avi* – *Polygonum aviculare*, *Vio arv* – *Viola arvensis*.

Due to the high number of measured soil properties, automatic forward selection of environmental variables was used to reduce the total number of 13 soil properties to seven (clay, silt, sand, AWC, SOC, pH and Mg), which together explained 30.7% of the weed variability (analysis a6, Tab. V.5). Further division of the selected explanatory variables indicate the explanatory power of the individual soil properties. The most decisive soil property affecting weed species composition was AWC (calculated for 1.5 m depth), which explained 17.4% of weed data variability (analysis a12), followed by clay (13.2%, analysis a9) and sand (12.4%, analysis a11) contents in the plough horizon. Additionally, SOC (8.4%, analysis a13) and silt (5.3%, analysis a10) contents also revealed a considerable explanatory power. The combination of these five soil properties with the highest individual explanatory power explained remarkable 28.2% of weed species variability (analysis a16). Considering all canonical axes, 30.9% of weed species composition can be explained by soil texture and SOC content in the plough horizon and AWC of the soil profile (analysis a16, Tab. V.5).

Tab. V.5: Results and statistical evaluation of redundancy analysis (RDA) of mean weed species abundance in relation to various soil properties of the plough horizon (except available water capacity, AWC: calculated for 1.5 m depth)

No.	Explanatory Variable	First canonical axis			All canonical axes		
		%	*F*	*P*	%	*F*	*P*
a5	SOC, N_t, clay, silt, sand, AWC, pH, P, K, Mg, POM1, POM2, POM3	34.0	217.1	0.001	39.7	21.0	0.001
a6	clay, silt, sand, AWC, SOC, pH, Mg	30.7	186.9	0.001	34.6	31.9	0.001
a7	Clay	13.2	64.9	0.001	-	-	-
a8	Silt	5.3	23.9	0.001	-	-	-
a9	Sand	12.4	60.3	0.001	-	-	-
a10	AWC	17.4	89.8	0.001	-	-	-
a11	SOC	8.4	39.1	0.001	-	-	-
a12	pH	3.6	16.1	0.001	-	-	-
a13	Mg	3.6	15.7	0.001	-	-	-
a14	clay, silt, sand, AWC, SOC	28.2	166.3	0.001	30.9	37.8	0.001

Figure V.4 visualises the result of analysis a16 (Tab. V.5) in the form of an ordination diagram. The abundance of *C. album* is positively affected by sand content and AWC, but negatively affected by clay content. In contrast, *P. aviculare* is positively correlated with the clay content and negatively correlated to AWC. Clay and silt content positively affected *V. arvensis*, which, in turn, is negatively correlated with the sand content. Grass weeds are particularly affected by silt content and AWC. Again, SOC indicates a high but non- directional effect on all observed weed species (Fig. V.4). This non-directional effect indicates the high complexity of soil properties, their interrelation and their complex effects on weed growth conditions.

Considering the ordination diagram, it seems remarkable that AWC and sand content positively affected each other and certain weed species, while AWC and clay content negatively affected each other and thus certain weed species (Fig. V.4). This apparent contradiction can be explained with the geological situation of the soil in the test field, as stated in section 3.2. Due to the different layering in soil and the different measurement depths, AWC as derived from EC_a for 1.5 m soil depth and soil texture in the plough horizon have to be interpreted separately for explaining weed species distribution.

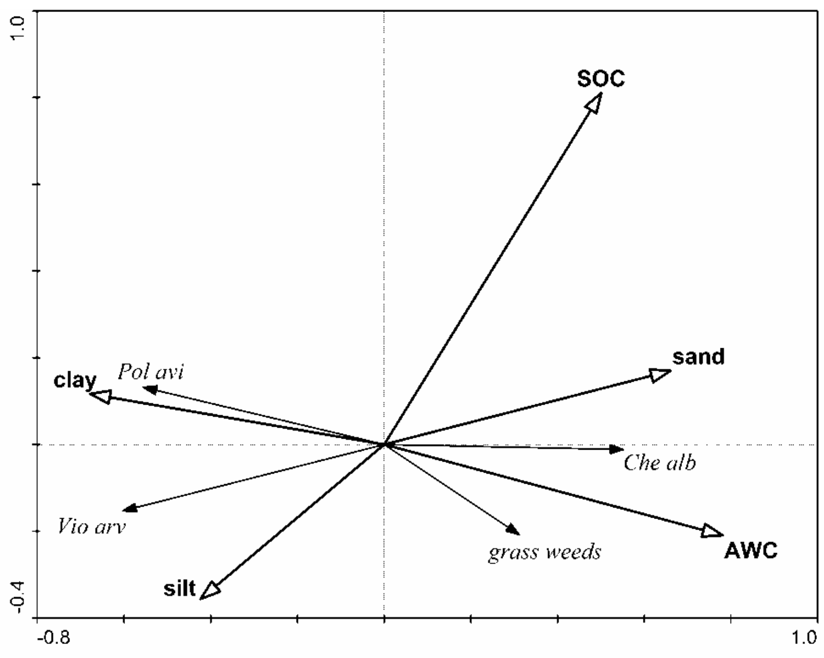

Fig. V.4: Ordination diagram visualising the results of the redundancy analysis (RDA) in which soil texture (clay, silt, sand), available water capacity (AWC) and soil organic carbon (SOC) were used as environmental (explanatory) variables. Species abbreviations: *Che alb – Chenopodium album*, *Pol avi – Polygonum aviculare*, *Vio arv – Viola arvensis*.

Weed species variability, especially for *C. album* and grass weeds – mainly *A. myosuroides* – was strongly affected by AWC, which describes soil water supply during periods with non-sufficient rainfall (Fig. V.1b, d, f; Fig. V.4). Roberts and Potter (1980) report that the absence of soil moisture restricts weed emergence. Mehrtens (2005) observed weed species preferring moist soil conditions and areas with deep moist horizons. Also wet-dry cycles affect weed emergence and longevity (Long et al., 2011). Even if weed estimation took place at the beginning of the vegetation period, some weeds usually emerge after herbicide application (Dicke et al., 2004; Gerhards et al., 2005). Furthermore, adult weed plants are able to reach the subsoil due to their often distinct root system. These weed plants produce new seeds and therefore stabilise spatial weed patterns at areas with favourable competitiveness for the individual species, such as high AWC during the growing season. Thus, the

AWC to 1.5 m soil depth potentially yields information on weed emergence, growth and competitiveness, finally resulting in a given weed abundance and density.

Besides, soil texture and SOC in the topsoil affected weed species variability (Fig. V.4). Soil texture and SOC are key parameters with complex interrelations that affect other soil properties such as soil porosity, aggregate stability, soil respiration or nutrient status, which, in turn, affect weed and crop growth. Higher sand contents mostly improve rooting, enhance porosity and related soil respiration as well as water conductivity. Less available soil water at higher sand contents can retard weed and crop growth at the beginning of the vegetation period.

Concerning the weeds under study, *C. album* as a thermophile weed is relative resistant to drought stress (Bruckner-Pertl et al., 2001) and therefore may benefit from a rather high competitiveness at sandy texture. Andreasen et al. (1991) observed a negative correlation between *C. album* and the clay content. These findings are in line with the presented results. The abundance of *P. aviculare* and *V. arvensis* was positively affected by topsoil clay and silt content in this study, respectively (Fig. V.4). In contrast, Andreasen et al. (1991), Walter et al. (2002) and Mehrtens (2005) related *P. aviculare* and *V. arvensis* abundance with lower clay or higher sand contents. Also *A. myosuroides*, the main grass weed in the test field of the present study, was associated to high clay contents (Nordmeyer and Niemann, 1992), which was also not in line with the presented results. These different results indicate once more the considerable complexity between weed species abundance and related soil properties. However, the soil is an important parameter for spatial weed distribution due to its function of modifying root zone, microclimate, water- and nutrient-supply (Nordmeyer and Häusler, 2004).

Apart from physical soil properties, the chemical soil property SOC affected weed species variability (Fig. V.4). Walter et al. (2002) confirm this effect on spatial weed distribution. The SOC content of the test field in the present study was rather homogeneous. The SOC content did not affect certain weed species at given positions within the field, but had a significant and uniform effect on all observed weed species. However, even the low SOC range implies a high effect on weed variability, which emphasises the importance of SOC. SOC indirectly affect weed distribution and density due to its effect on other soil constituents, such as the water holding capacity or the nutrient status of the soil (Andreasen et al., 1991; Nordmeyer and Häusler, 2004). More research seems necessary to evaluate the effect of SOC on spatiotemporal weed species variability.

Multivariate analysis such as RDA can be adequately used to improve the complex relations of various fields of research such as weed and soil science. Relationships between soil properties and weed species can be determined within the multi-dimensional space of RDA. It further takes the complexity of soil properties among each other and this effect on different weed species into account, which is not possible with one-dimensional data analysis. It is therefore suggested that multivariate analysis such as RDA should be more frequently used when interdisciplinary questions are observed. Based on the results from RDA weed management maps were further created to improve site-specific weed management.

3.5 Weed management maps for site-specific weed management

Weed management maps aim at a site-specific management of weeds in order to save herbicides for ecological and economical benefits and are required within the scope of precision crop protection. Weed maps displaying the spatial weed distribution and density for subsequent patch spraying of herbicides can be frequently found in literature (e.g. Dicke et al., 2004; Gutjahr et al., 2008; Kroulik et al., 2008). Gerhards and Oebel (2006) and Weis et al. (2008) already demonstrated weed maps for decision algorithms for site-specific weed management and patch spraying. Nevertheless, the effect of soil heterogeneity have not been taken into account, even if its effect on weed variability has been proven in this study and also partially in other studies before (Andreasen et al., 1991; Walter et al., 2002; Nordmeyer and Häusler, 2004). However, non-invasive and minimal-invasive soil sensors are meanwhile available to detect soil properties in a fast and convenient way. Thus, weed management maps on the basis of soil maps with regard to spatial weed distribution based on the results of RDA (Fig. V.4) were created in order to elaborate a novel basis for site-specific weed management.

The sand content of the topsoil affected the variation in *C. album* and *V. arvensis* – as shown above. The higher was the sand content, the higher was the density of *C. album* and the lower was the density of *V. arvensis*, respectively. *P. aviculare* and grass weeds were primarily affected by AWC. The lower was the AWC, the higher was the abundance of *P. aviculare* and the lower was the abundance of grass weeds, respectively. Thus, two soil maps were generated displaying the sand content in the plough horizon and the AWC in the main root zone of the test field. The displayed sand content was divided into two areas with low (< 18%, area 1) and high (> 18%, area 2) sand content (Fig. V.5a). The visualised AWC was divided in three areas with low to medium (< 140 mm, area 1), high (140 – 200 mm, area 2) and extremely high (> 200 mm, area 3) AWC (Fig. V.5b).

The averaged abundance of the observed weed species within the different areas and with respect to the economic weed thresholds are shown in Figures V.5c and V.5d. For the determination of an appropriate economic weed threshold, the description of Dicke et al. (2004) was taken into account, who suggested 10 plants m^{-2} for dicots and 6 plants m^{-2} for monocots as reasonable economic thresholds. While *V. arvensis* exceed the economic weed threshold in area 1 of the sand content map (low sand content), *C. album* does not reach it, which was *vice versa* in area 2 (high sand content, Fig. V.5c). *P. aviculare* exceed the economic weed threshold in areas 1 and 2 (low to medium and high AWC), while the grass weeds do not reach the economic threshold in any of the areas (Fig. V.5d).

Economic weed thresholds are target values which help farmers to decide if herbicide application is necessary or not. Soil maps as displayed in this study can serve as weed management maps. Depending on the field crop and on site-specific knowledge of the farmer, the indicator weed can be determined and the appropriate soil map can be taken into account.

On the basis of such soil maps, full, reduced or no herbicide dosages can be applied on different areas of the field. Thus, weed management maps on the basis of soil information may help calculating the site-specific usage and dosage of herbicides. Site-specific application of herbicides with respect to soil texture zones and SOC contents reduce environmental burden, due to their effect on herbicide efficacy and leaching (Walter et al., 2002; Patzold et al., 2008). Site-specific weed management performed with patch-spraying after automated weed counting (e.g. by image analyses) can also reduce the amount of herbicides used (Gerhards et al., 2005; Weis et al., 2008), but without considering the effect of soil heterogeneity on herbicide behaviour.

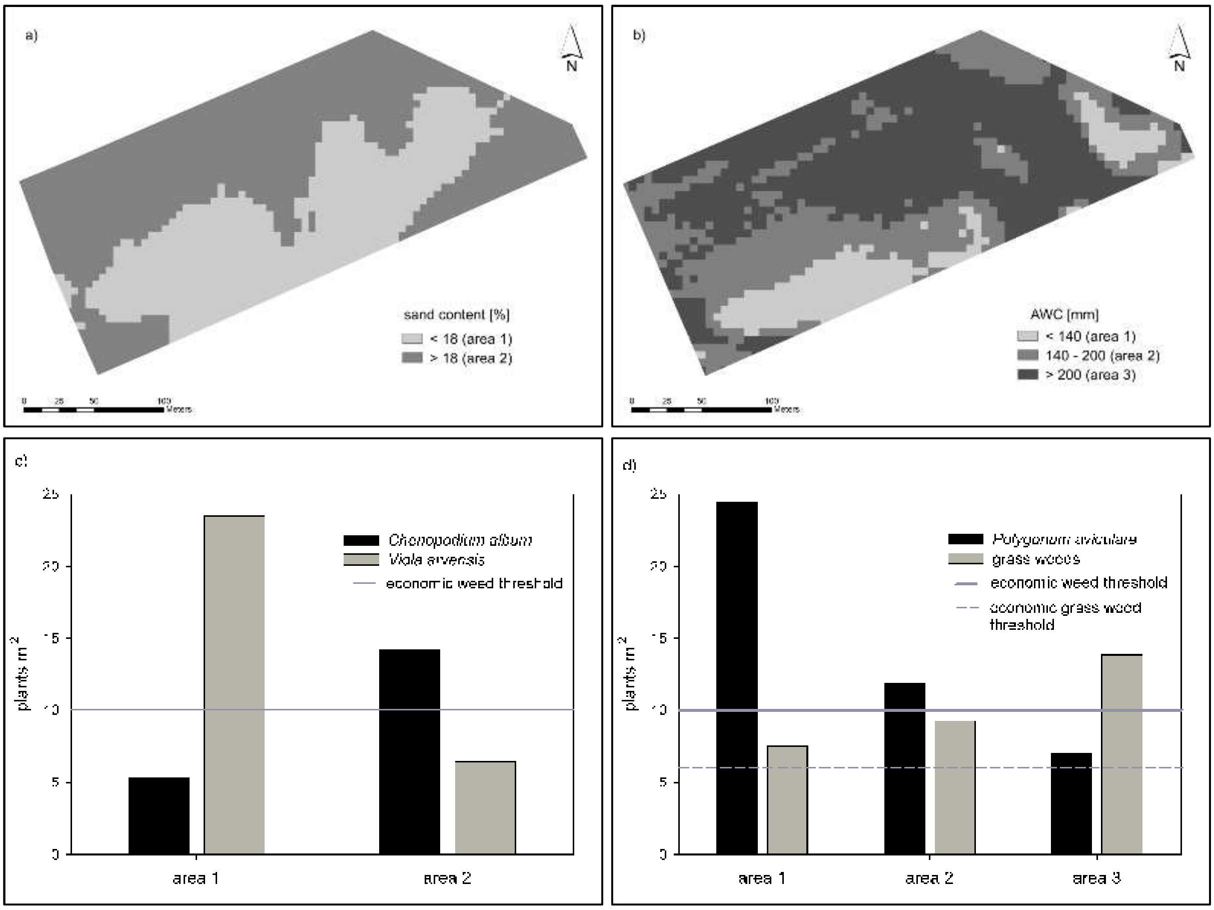

Fig. V.5: Weed management maps on the basis of soil maps for site-specific weed management and related mean abundance of weed species: a) map of the sand content in the plough horizon, b) map of the available water capacity (AWC) in the main root zone, c) mean abundance of *Chenopodium album* and *Viola arvensis* within the different areas of the sand content map with respect to the economic weed threshold d) mean abundance of *Polygonum aviculare* and grass weeds within the different areas of the AWC map with respect to the economic weed thresholds. The economic weed thresholds were adapted from Dicke et al. (2004).

Weed management maps as shown exemplarily for the test site under study can be created for other arable fields with patchy weed distribution. Weed patches are stable over time, which was successfully demonstrated in a long-term survey over a period of nine years, and is known from some previous projects (Gerhards and Christensen, 2003; Mehrtens, 2005; Dicke et al., 2007). Soil texture, AWC and SOC can be regarded as stable over time as well. The soil maps can be combined with the determination of weeds using image analyses to improve prospective site-specific weed management. However, beside soil properties, weed species abundance is affected by other parameters such as field crops or climatic conditions. Due to the ability of weeds to adapt to a wide range of ecological conditions (Andreasen et al., 1991), further analysis are necessary to obtain relationships between weed species and soil properties. It should be examined if the presented results can be verified under consistent climatic conditions in identical field crops. Relationships between soil properties and weed species variability may be validated for certain regions.

Furthermore, the results of RDA and the displayed maps contribute to a better understanding of site-specific interrelations between weeds and soil properties and thus the patchy occurrence of weeds. The dominant soil properties affecting weed species distribution, namely AWC, soil texture and SOC, can be detected fast and convenient via new sensor technologies such as EM38 and MIRS-PLSR. While the EM38 is a non-invasive technique to detect texture related spatial soil heterogeneity in the field, soil samples still need to be taken for analyses via MIRS-PLSR. It is further assumed that other non-invasive technologies, such as site-specific SOC determination via airborne hyperspectral imaging (cf. section III) will displace soil sampling in the future.

4 CONCLUSIONS AND PERSPECTIVES

Within a nine-year survey it could be supported that weed patches and their relations to soil properties within arable fields are stable over time. Beside environmental factors such as certain field crops, soil tillage or climatic conditions, soil heterogeneity affects weed species distribution and abundance. The combination of soil sensing technologies and multivariate statistics revealed an unexpected strong effect of soil properties on weed variability that was only scarcely documented in literature before.

With regard to the complex interrelations of soil properties, multivariate analyses revealed that mainly soil texture, AWC and SOC, which affect plant available water and nutrient contents, affect weed species variability. Those soil properties in the required data density can be detected fast and convenient with non- or minimal-invasive technologies such as EM38 or MIRS-PLSR. Other non-invasive technologies such as hyperspectral imaging should be applied for further investigations on the determination of soil properties with a high spatial resolution.

Several benefits are expected from soil-based weed management maps for site-specific weed management:

(i) Site-specific interrelations between soil properties and the patchy occurrence of weeds become more comprehensible, which improves site-specific weed control in general and contributes to the further development of precision crop protection.

(ii) Sampling strategies can be improved. Weed counting as well as soil sampling can be reduced due to the stability of weed patches and soil properties over time.

(iii) Site-specific herbicide application can be reduced. Due to the effect of soil properties on herbicide efficacy and leaching, herbicide dosages can be optimised with knowledge about soil textural zones and SOC distribution.

VI

Synthesis and Perspectives

1 RELEVANCE OF SOIL FOR PRECISION CROP PROTECTION

One major challenge for applied precision crop protection, which is a significant part of precision agriculture, is the quantification of soil heterogeneity at the field-scale. Heterogeneity at the field-scale affects crop growth, but is also important for the development of pests and diseases (Mahlein et al., 2010; Hillnhütter et al., 2011b) as well as weeds (Dicke et al., 2004; Gerhards and Oebel, 2006). If the heterogeneous occurrence of pests or weeds can be traced back to soil parameters, pesticide applications can be adjusted to the variability of soil properties (Patzold et al., 2008). The spatial heterogeneity of soil properties is of particular importance for site-specific crop protection, as it interacts in a multiple and complex way with various crop-protection aspects. SOC and soil texture are particularly important key soil properties influencing other soil parameters as well as crop and pest development and the environmental behaviour of pesticides. Thus, the exact determination of soil variability at the field-scale can improve site-specific management decisions. Management maps are required by agronomists and farmers to manage land in a sustainable and site-specific way, which is optimal adapted to environmental and agricultural needs (Oliver and Webster, 1991; Viscarra Rossel and McBratney, 1998). However, such maps on the basis of heterogeneously distributed soil properties are not available yet for practical use, even if soil sensors become more and more available.

The aim of this PhD-thesis was to clarify the multiple effects of soil properties and their heterogeneous distribution within fields to crop protection problems. Furthermore, the aim was to contribute to the improvement of precision crop protection in each of the major fields, namely general crop and pest development, soil-borne pests and weeds. Therefore, the foci of this study were (i) the improvement of SOC detection via hyperspectral airborne imaging, (ii) the survey of relationships between soil texture measured via electrical conductivity and the occurrence of the plant parasitic cyst nematode *H. schachtii* and (iii) the temporal stability of weed patches and their relation to heterogeneity of soil properties within a long-term survey using innovative technologies. One further focus was the creation of management maps on the basis of soil heterogeneity to improve site-specific management within precision crop protection.

2 SOIL ORGANIC CARBON HETEROGENEITY DETECTED WITH AIRBORNE HYPERSPECTRAL IMAGING

The results reveal an overall high prediction accuracy of topsoil SOC at the field-scale using airborne hyperspectral imaging with the HyMap sensor and MIRS-PLSR. Site-specific differences were observed concerning prediction accuracy with respect to various soil surface conditions. Rough soil surfaces and vegetation or straw residues decrease the prediction accuracy, whereas low surface roughness and the absence of vegetation and straw residues increase the prediction accuracy. Thus, freshly prepared seed-beds or ploughed soils lead to almost optimal conditions for airborne reflectance spectroscopy. Due to the high spatial resolution of the HyMap sensor, a pixel-based map (8×8 m $\triangleq$ mean of four pixels, each 4×4 m) was generated visualising the small-scale variability of SOC contents more realistically than interpolated maps.

Airborne hyperspectral imaging is a new approach for precision crop protection as well as for soil C monitoring. The SOC variability of arable fields could be detected at a small spatial scale. The preciseness of airborne hyperspectral imaging was adequate to that of a conventional sampling and laboratory analysis (RMSECV = $\pm$ 1.05 g SOC kg^{-1}). It is expected that local calibrations with respect to local circumstances of the soil (e.g. various texture) and to varying surface conditions further enhance the accuracy of the results. However, the accurate pixel-wise prediction of SOC displayed in management maps without the need of geostatistical treatment seems especially reasonable for precision agriculture practices and soil C monitoring.

Hyperspectral imaging for the measurement of SOC was conducted on more or less bare soil surfaces because of the highest prediction accuracy under these circumstances. However, bare soil surfaces are seldom available on many fields at the same time and also rarely during summer, when there are optimal weather conditions for flight campaigns. Thus, specific analytical methods such as linear spectral unmixing should be used in future to reduce the effect of vegetation and straw residue covers with simultaneous improvement of the prediction accuracy (Bartholomeus et al., 2011). The prediction accuracy can further be improved by the use of different sensors such as ROSIS or AISA sensor systems, which offer a higher spatial resolution than the HyMap sensor (Bartholomeus et al., 2007; Késmárki-Galli et al., 2009). Another alternative is the use of an unmanned aerial vehicle (drone) instead of an aircraft for hyperspectral measurements, which cause only low costs and can be driven individually at desired dates, fields and weather conditions (Johnson et al., 2004). Adequate low-weight sensors are already under development.

With respect to the multiple effects of SOC, high-resolution SOC maps can improve digital soil mapping. Related soil properties should be estimated via pedotransfer functions on the basis of SOC contents. In addition, digital elevation models and geostatistical methods such as co-kriging can be used to improve digital soil mapping (McBratney et al., 2003; Behrens et al., 2010). López-Lozano et al. (2010) recently presented how spatial soil and plant data from remote sensing techniques can be integrated to site-specific management within precision agriculture.

SOC maps based on airborne hyperspectral imaging are characterised by a high spatial resolution of a few m^2. Site-specific management decisions within precision crop protection can be improved due to the effect of SOC on other soil constituents, crop stand parameters, preferences of pests and weeds as well as on the behaviour of pesticides in soil. E.g., fertiliser and pesticide applications can be optimised in a site-specific way. Additionally, the survey of SOC contents and SOC pattern stability benefits soil C monitoring with regard to the detection of agricultural soils as sources or sinks for carbon.

3 DETECTION OF NEMATODE PATCHES WITH A NON-INVASIVE SOIL SENSOR

The study ought to test the hypothesis that (i) the patchy distribution of the plant parasitic beet cyst nematode (BCN) *H. schachtii* within sugar beet fields is linked to the spatial variability of soil conditions and that (ii) this variation can be detected by a non-invasive soil sensor. Areas with homogeneous or heterogeneous soil texture can be indicated by measurements of the apparent electrical conductivity (EC_a) with the non-invasive EM38 sensor within agricultural fields. Due to the missing depth information of EC_a measurements, additional information from soil taxation maps improved the knowledge on the vertical variability in soil. The results indicate that arable fields, infested with *H. schachtii* and heterogeneous in soil texture, reveal a close relationship between spatial patterns of *H. schachtii* cysts and EC_a. Highest cyst densities were observed at low EC_a values and thus at deeper and / or light to medium textured (i.e. sandy) soils. Favourable environmental conditions for BCN development, such as adequate pore size, soil moisture conditions at field capacity and rapid warming of the soil in the spring, are provided in these soils. However, the layering of soil cannot be detected by EM38 in all cases, but can determine BCN-relevant soil properties, e.g. stagnic properties. Thus, additional information from soil maps (as reveal with soil taxation maps in this study) or a local calibration can improve the assessment of BCN living conditions. Management maps were created on the basis of EC_a data and information from soil taxation maps and were compared with the observed spatial nematode distribution.

Measuring EC_a is a fast and convenient method to detect the spatial heterogeneity of soil texture and soil porosity and it can be concluded that it is a useful tool to develop maps for nematode management in terms of a risk assessment. Such maps on the basis of EC_a data enable farmers to apply suitable management strategies with ecological and economic benefits, such as site-specific sowing of resistant cultivars or site-specific nematicide application, if nematicides are authorised. Furthermore, management decisions and preventive measures on the basis of these maps can be conducted before the growing season starts. Thus, management maps based on the EC_a

values indicating zones of varying nematode risks on heterogeneous fields are highly appropriate for site-specific management of *H. schachtii*-infested sugar beet fields and offer new advantages to farmers.

Innovative techniques such as EC_a measurements and hyperspectral data imaging should be combined in future studies to further improve site-specific nematode management. Hillnhütter et al. (2011b) successfully detected BCN patches on the basis of above-ground symptoms at sugar beet plants during the growing season using airborne hyperspectral imaging. The use of additional non-invasive data can thus improve the spatial resolution of management maps. The small-scale variability of nematode patches can be determined with a higher accuracy using high-resolution data from multiple non-invasive sensors.

It is further assumed that management maps generated with the described procedure may also be transferred to other crops and plant parasitic nematodes such as *D. dipsaci* on sugar beet or *P. penetrans* on maize, and as well on fungal plant pathogens such as *R. solani*, if a proven relationship to soil texture is observed. However, this assumption needs to be proven on different agricultural fields in additional consideration of other soil properties than EC_a, due to possible preferences of other pests to other soil parameters.

4 THE USE OF MINIMAL- AND NON-INVASIVE SENSOR TECHNOLOGIES TO DETECT SPATIOTEMPORAL WEED DYNAMICS AS AFFECTED BY SOIL PROPERTIES

The heterogeneous distribution patterns of four weed species within an agricultural field turned out to be very stable over a period of one decade. Based on this observation it was hypothesised that soil conditions, being spatial heterogeneous as well, have a significant effect on the (non-)appearance of weeds. EM38 measurements and MIRS-PLSR were used to determine soil properties within the long-term weed survey, namely N_t, SOC, POM1, POM2, POM3, pH, clay, silt and sand as well as the plant-available nutrients P, K and Mg. Due to the specific conditions of the test field, not only depth-averaged soil texture but also available water capacity (AWC) could be derived from EC_a data. Multivariate statistics in the form of redundancy analysis (RDA) was used to explain the effect of environmental variables (years, field crops and soil properties in this study) on weed data variability. Results of the RDA reveal that the temporal stable weed species distribution was significantly affected by the environmental parameters soil properties, field crops and various years. However, spatial heterogeneous weed patches and thus weed data variability could be adequately explained by various soil properties. On closer examination, almost one third of weed species composition could be explained by the soil properties texture, AWC and SOC. In the light of the various parameters affecting weed abundance, this was an unexpected strong result. Preferences of single weed species for specific soil properties became visible in an ordination diagram. Based on these results, weed management maps for site-specific weed management were created on the basis of soil maps.

The most popular site-specific weed management approaches are by now weed management maps in combination with patch spraying (Dicke et al., 2004), weed detection with image analyses (Gerhards and Oebel, 2006) or computerised decision algorithms (Ritter et al., 2008). The strong effect of soil properties was not considered accurately in the past due to the time- and cost-intensive determination of soil properties. Here, the sensor application allows for new, innovative approaches which take soil into account. Furthermore, the dominant soil properties affecting weed patches, namely AWC, soil texture and SOC, can be detected fast and convenient via ambitious technologies such as EM38 and MIRS-PLSR. These soil properties not only affect weed variability, they also affect the sorption, efficacy, degradation and leaching of pesticides. Therefore, weed management maps including soil information can further improve site-specific herbicide applications. Adapted herbicide applications can be performed before the growing season starts to prevent the emergence of weed seedlings. It is further assumed that other non-invasive technologies, such as site-specific SOC determination via airborne hyperspectral imaging, can be used to determine soil heterogeneity in the future.

Due to the high adaptability of weeds to environmental conditions, it should be examined if the presented results can be verified under consistent climatic conditions in identical field crops. Relationships between soil properties and weed species variability may be validated for certain regions. Furthermore, it should be tested if the observed local relationships can be transferred to totally different environmental conditions.

5 GENERAL CONCLUSIONS

The presented results reveal that soil properties and their heterogeneity at the field-scale affect precision crop protection, which was not considered in the past due to methodological limitations. As examples, the SOC content, the occurrence of the plant parasitic cyst nematode *H. schachtii* and weed species distribution and densities were examined in this study. Spatial soil variability can easily be detected by various sensor techniques and should be taken into consideration for prospective precision crop protection. Management maps on the basis of soil constituents, detected with minimal- or non-invasive sensors, will help agronomists and farmers to manage an entire field in a site-specific, effective way. Hence, ecological and economic benefits for famers are offered, even if a cost-benefit calculation is almost impossible for precision crop protection at the current state of research.

Further improvements will be achieved by the combination of different sensor techniques when examining on distinct soil properties as well as on related (soil-borne) pests or weeds. Therefore, existing sensors techniques should be improved, as shown exemplarily for the use of a pedotransfer function to derive the available water capacity from EC_a values under specific site conditions as explained in this study. In addition, new technologies should be further examined. One promising technique to determine SOC content in the topsoil is the non-invasive gamma-ray spectroscopy (Wielopolski et al., 2008). Nevertheless, future approaches should focus on the development of on-the-go sensors, e.g. for the direct measurement of SOC within fields with the use of VIS/NIR spectroscopy. Schirrmann et al. (2011) recently introduced an on-the-go sensor for high-resolution mapping of soil pH at the field-scale. However, even if these new technologies are promising for future soil mapping, information about soil heterogeneity in deeper soil horizons are still limited. As shown in this study, soil properties in the subsoil such as soil texture and porosity or available water capacity are important parameters affecting the spatial distribution of *H. schachtii* and weed variability. Therefore, another important aspect regarding new sensor technologies to detect spatial soil variation should focus on the depth-resolution.

However, important soil properties such as soil texture and SOC are stable parameters over time, as shown for SOC in this study. This fact as well as the fast and convenient use of sensors indicates the possibility of measuring soil properties in regular intervals under consistent conditions, improving the cost efficiency of these measurements. Precision crop protection can be improved and innovative soil monitoring processes can be initiated. As shown, this is even possible without using geostatistics, but on a simple pixel-wise basis. The presented results contribute to precision crop protection as well as to soil monitoring, facing the major challenges of agricultural production today and in future.

VII

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