Linking weed patterns with soil properties: a long-term case study

Stefan Pätzold¹ · Christine Hbirkou^{1,2} · Dominik Dicke^{3,4} · Roland Gerhards⁵ · Gerhard Welp¹

Published online: 21 September 2019
© The Author(s) 2019

Abstract

The spatial distribution and density of different weed species were monitored during a long-term survey over a period of 9 years on a 5.8 ha arable field and related to soil properties. Weed seedlings were determined every year in spring on a regular grid with 429 observation points (15 × 7.5 m; net study area = 4 ha). Dominant weed species were *Che-nopodium album*, *Polygonum aviculare*, *Viola arvensis* and different grass weeds, clearly dominated by *Alopecurus myosuroides*. A non-invasive electromagnetic induction survey was conducted to evaluate available water capacity directly in the field at high spatial resolution. Further soil properties were evaluated following the minimum-invasive approach with soil sampling and subsequent mid-infrared spectroscopy. Plant available nutrients were analysed with conventional lab methods. Redundancy analysis served to describe the effect of soil properties, different years and field crops on weed species variability. Seven soil properties together explained 30.7% of the spatial weed species variability, whereas 28.2% was explained by soil texture, available water capacity and soil organic carbon. Maps for site-specific weed management were created based on soil maps. These maps permit several benefits for precision crop protection, such as a better understanding of soil–weed inter-relations, improved sampling strategies and reduction in herbicide use.

Keywords Heterogeneity · Apparent electrical conductivity (EC_a) · Mid-infrared spectroscopy (MIRS) · Redundancy analysis (RDA)

✉ Stefan Pätzold
s.paetzold@uni-bonn.de

¹ Institute of Crop Science and Resource Conservation (INRES) – Soil Science and Soil Ecology, University of Bonn, Nussallee 13, 53115 Bonn, Germany

² Present Address: Federal Office for Agriculture and Food, Deichmanns Aue 29, 53179 Bonn, Germany

³ Institute of Crop Science and Resource Conservation (INRES) – Crop Science, University of Bonn, Katzenburgweg 5, 53115 Bonn, Germany

⁴ Present Address: Regional Administrative Authority Gießen, Plant Protection Service Hesse, Schanzenfeldstraße 8, 35578 Wetzlar, Germany

⁵ Department of Weed Science, Institute of Phytomedicine, University of Hohenheim, 70599 Stuttgart, Germany

Introduction

Weeds cause significant damage to crops in arable fields around the world with typical yield losses ranging between 10 and 80% (Marshall et al. 2003; Oerke and Dehne 2004; Gerhards et al. 2017). Weed control is challenging, because weed populations can vary spatially and temporally and adapt very quickly to new management and control strategies (Sosnoskie et al. 2006). Weeds and crops compete for light, water and nutrients (Cousens and Mortimer 1995; Kobusch 2003; Ritter et al. 2008) in a complex way; individual competitiveness is both crop- and weed-specific as well as site- and year-dependent (Kobusch 2003). Field crops with slow juvenile development (e.g. maize, sugar beet) are more susceptible to weed competition at early development stages than field crops with rapid juvenile development (such as cereals and rape) (Cousens and Mortimer 1995; Gerhards et al. 2017). Year-dependent weed density can be affected by soil tillage and climatic conditions (Cousens and Mortimer 1995; 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 often occurs within arable fields as reviewed by Rew and Cousens (2001); this phenomenon has been the objective of many studies (e.g. Gerhards and Oebel 2006; Ritter et al. 2008; Metcalfe et al. 2016; Korres et al. 2017).

Occurrence and spatial pattern of weeds depend on various environmental and human-induced factors. Minimum and no tillage practices increase weed density which, in turn, can be reduced by ploughing (Bàrberi and Lo Cascio 2001; Cardina et al. 2002). Crop rotation has a significant effect on weed occurrence (Cardina et al. 2002). Differences in weed species composition have been 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 modified by herbicide application in different ways (Dieleman et al. 1999; Squire et al. 2000). Finally, crop stand parameters affect weed density (Chhokar et al. 2012; Mhlanga et al. 2016).

Weed patches are often stationary over years (Gerhards and Christensen 2003; Kulkarni et al. 2017; Malmstrom et al. 2017). Several authors have observed relationships between the patchy distribution of various weed species and spatial soil heterogeneity. Soil organic carbon (SOC), soil texture and nutrient status of the soil mainly affect weed occurrence (Gaston et al. 2001; Nordmeyer and Häusler 2004; Korres et al. 2017). Various soil properties are closely inter-related, so that a given parameter such as soil organic matter can be an indicator for other soil conditions, such as water holding capacity. Thus, soil properties affect weed growth in a rather complex way and one must take various inter-relations into account (Andreasen et al. 1991).

Gerhards and Christensen (2003) reviewed approaches to optimise site-specific weed control. Gerhards et al. (2005) as well as Gutjahr et al. (2008) conducted on-the-go detection of weeds and successfully used the data for automated patch spraying. Weed detection studies were not only conducted vehicle-based (Weis et al. 2008; Pantazi et al. 2016), but also airborne (Gray et al. 2008; Malmstrom et al. 2017) or satellite-based (Jacobi et al. 2006). Underlying principles were spectral (Pantazi et al. 2016; Schmittmann and Schulze Lammers 2017) or image analyses (Gerhards and Oebel 2006), occasionally in combination with computerised decision algorithms and modelling or deep learning approaches (Christensen et al. 2003; Ritter et al. 2008; Ferreira et al. 2017). However, detailed economic benefit of weed detection is still to be evaluated (Franco et al. 2017). Geostatistical

analyses with varying interpolation techniques are also applicable in weed research (Webster 2010). Kroulik et al. (2008) combined different approaches and included soil information on the basis of apparent electrical conductivity (EC_a) measurements, resulting in a satisfactory predictive accuracy for *Cirsium arvense*. Recently, Big Data approaches are being used, but more data, especially on soil, are still required to reliably predict weed occurrence (van Evert et al. 2017). Up to now, reliable long-term weed data that are correlated to soil properties are still scarce, although soil sensing techniques allow for recording soil data at high spatial resolution.

The correlation between soil properties and weed occurrence and abundance is the scope of this study. Soil properties were to be characterized at high spatial resolution and low efforts to evaluate their effect on weeds. Prerequisites for this approach were the use of different sensor technologies and multivariate statistical methods. Among others, SOC, total nitrogen content (N_t), texture and mineralogical composition have been successfully determined via sensing technologies (Kuang et al. 2012). Thus, it was hypothesised that it should be possible to identify and quantify the effect of soil on weed species composition, spatial distribution and density (in the following altogether denoted as weed variability) by the use of sensing technologies. For this purpose, long-term data of a nine-year weed survey at 429 grid points on an experimental field with a regular crop rotation were re-evaluated. Weed management maps on the basis of sensor data and soil maps were created in order to demonstrate the potential of sensor-based soil information for site-specific weed management.

Materials and methods

Test field

The weed survey was conducted on an arable field of 5.8 ha size (including edges and headlands) at the Dikopshof Research Station of the University of 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 followed by winter barley) comprised the crop rotation on the test field. This uniform 4-year crop rotation was consistent with plough tillage and homogeneous fertilisation for the past several decades.

The test site is characterised by considerable soil heterogeneity (Mertens et al. 2008). Detailed soil profile data have been provided by Pätzold and Welp (2009). Soils developed from loess and sandy-gravelly alluvial sediments overlying the sandy-gravelly, 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, loess loam or Pleistocene terrace sediments. Thus, soil texture and porosity vary over a wide range. Soil types alternate, according to the World Reference Base for Soil Resources (IUSS 2015), between Haplic Cambisols, Luvic Cambisols, Haplic Luvisols and Colluvic Regosols.

Experimental design for weed determination

Weed seedlings were determined every year in spring along a regular grid (15 × 7.5 m; n = 429, overall size approximately 4 ha) prior to herbicide application from 1998 to

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 to 2003 on the entire test field of 5.8 ha size (Dicke et al. 2007), but evaluated only along the grid of 4 ha size. This experiment did not lead to an increase of weed abundance (Dicke and Kühbauch 2006). The grid of that study was maintained in the test field throughout the study years. Weed seedlings were counted in a 0.4 m² frame placed at all intersection points (n=429, Fig. 1a). While broadleaved weeds (dicots) were separated into each occurring species, all monocot species were summed up and counted as grass weeds, because the grass weeds were clearly dominated by *Alopecurus myosuroides* (Huds.).

Soil sampling and spectral analyses

Soil samples were taken from 0 to 0.3 m depth (plough horizon) with an auger at the end of the long-term weed survey at the grid points (n=429). A single sampling date was considered sufficient because the soil properties under study are stable over time, at least for the period of the weed survey. The spatial co-ordinates were recorded using differential GNSS. Due to the high total number of samples, only plant available nutrients were conventionally analysed in all samples. For the other soil parameters [except available water capacity (AWC), see below], a core set of 127 soil samples was randomly selected and analysed with conventional laboratory methods; the core samples served for mid-infrared spectroscopy (MIRS) model calibration (see related section below). All soil samples were air-dried, sieved (< 2 mm) and milled for subsequent evaluation using MIRS (Bruker Tensor 27, Bruker Optik, Ettlingen, Germany). This technique based on diffuse reflection is a fast and cost-effective method to determine various soil properties, as reviewed by Viscarra Rossel et al. (2006). Model calibration for each soil property under study was conducted through leave-one-out cross validation and subsequent test-set validation via partial least squares regression (PLSR) using the OPUS QUANT software (Bruker Optik, Ettlingen, Germany). The conventionally analysed soil properties of the core sample set served as reference. The calibration procedure was described in detail by Bornemann et al. (2008).

Physical soil properties

Soil texture in the core sample set was determined by the combined sieving and sedimentation method (ISO 2002). Additionally, the apparent electrical conductivity (EC_a) was measured directly in the field via electromagnetic induction (EMI) using the non-invasive EM38 sensor (Geonics, Mississauga, Canada). The measurements were repeated several times during the long-term survey in order to level out the influence of timely variable soil moisture and to obtain a stable pattern of EC_a. All measurements were conducted in the EM38 vertical mode. That way, the obtained signal integrates influencing soil properties over roughly 1.5 m depth; however, the relative signal contribution is not linear over depth, and measuring depth is not clearly delimited (Corwin and Lesch 2003). Nonetheless, the vertical-mode EM38 signal provides essential contributions to AWC estimation even when more model inputs are available (Gooley et al. 2014). A detailed description of the repeated measurements for this field was given by Mertens et al. (2008).

Two geological layers occurred at the test field: silt-dominated loess with variable proportions of fluvial sediments overlaid sandy and gravelly fluvial sediments (Pätzold and Welp 2009). In consequence, soil texture over depth and EC_a values differed markedly. Mertens et al. (2008) suggested using EC_a data to predict further soil properties via pedotransfer functions. Due to the given geological situation, the AWC could be estimated from EC_a values. Thus, in this special case, AWC in mm was related to 1.5 m soil depth (i.e., the main root zone) on the basis of EC_a with supplementary local calibrations (i.e., the depth profiles of texture). The AWC is the plant available water in soil pores of medium size (0.2–10 μm) and was considered as indicator for the duration of water supply to crops and weeds during dry periods, because the soils under study had neither stagnic nor gleyic properties.

Conventional analyses of chemical soil properties

Total carbon and nitrogen (C_t , N_t) were determined with an elemental analyser Fisons NA2000 (CE Instruments, Milan, Italy). The plough horizon of the entire field was free of carbonate; in consequence, C_t corresponded to SOC. Plant available P and K were determined using the calcium-acetate-lactate (CAL) method. In the following, the available nutrients are denoted as P-CAL and K-CAL, respectively. Magnesium was extracted with 0.01 M CaCl_2 solution (Mg-CaCl_2). Soil pH was measured potentiometric in a 0.01 M CaCl_2 suspension.

Data analysis

Multi-dimensional data such as population or environmental properties can be successfully analysed using multivariate ordination techniques (Lepš and Šmilauer 2003). This method has been established in soil–plant research (Hejerman et al. 2010; Šrek et al. 2010) and can also be adapted to weed science (Pinke et al. 2009; Hyvönen et al. 2010; Ahmad et al. 2016). Redundancy analysis (RDA) was performed with the CANOCO 4.5 program (ter Braak and Šmilauer 2002) to evaluate the effect of various so-called environmental variables (CANOCO terminology) on the spatial variation of weed species density. These variables were—partially interacting—physical and chemical soil properties and other parameters (crop, year). Note that the latter variables comprise complex information about, e.g., water consumption of the crop, seeding and harvest dates, start and length of the vegetation period, and weather conditions. A pre-test in the form of a detrended correspondence analysis (DCA, with segmental detrending) 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 (cf. ter Braak and Prentice 1988). The environmental variables were considered in the form of categorical predictors (cf. Lepš and Šmilauer 2003). This means that all soil data from the 429 grid points were classified into categories, as, for example, shown for the EC_a -based AWC values in Fig. 1b. In RDA, such classified environmental variables are statistically handled like experimental treatments in a classical plot experiment, i.e. each class of every variable is regarded as a factor level in a factorial design. It is a prerequisite that these factor levels (or “environmental variables” in the RDA nomenclature) are constant over time. However, this assumption had been made for the soil properties (see above). All 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) affects another set of variables (weed data variability). According to Lepš and Šmilauer (2003), the relative importance of the canonical axes decreases from the first 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 Monte Carlo permutation test performed 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 in Lepš and Šmilauer (2003).

Spatial heterogeneity of weed patches for all years under study was analysed with the exploratory tool ‘Geographically Weighted Regression’ (GWR) in ArcGIS Editor 9.3 (ESRI Redlands, USA) following the instructions of 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 positioned regularly within a grid. The bandwidth with the best prediction accuracy was determined with the corrected Akaike Information Criterion (AICc) that allows GWR model optimization as reported by Liu et al. (2015). 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 23 software (IBM Corporation, 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. The displayed maps were created with ordinary kriging using ArcGIS Editor 9.3.

Results and discussion

Physical and chemical soil properties

Topsoil texture and SOC content were predicted with high accuracy via mid-infrared spectroscopy (MIRS). The coefficient of determination ($R^2=0.92\text{--}0.99$) as well as the root

mean square error of cross validation ($RMSE_{CV}=2.30$ to 17.5 g kg^{-1} for texture parameters, and 0.21 g kg^{-1} for SOC), the ratio of performance to deviation ($RPD=3.53$ to 8.31) and the root mean square error of prediction for the 30% test-set validation ($RMSE_p=2.70$ to 21.1 g kg^{-1} for texture parameters and 0.20 g kg^{-1} for SOC) corroborate the excellent quality of the calibration models. Prediction of pH values was satisfactory (Table 1). Consequently, MIRS-based soil data were reliable enough to serve as a basis for further investigation and topsoil texture, SOC and pH were predicted for the entire sample set.

The spatial distribution of soil properties revealed different degrees of heterogeneity within the test field; Table 2 presents related statistical parameters. The AWC of 1.5 m soil depth ranged from 57 to 426 mm and thus revealed high variability (CV 36%). It should be noted that the AWC was estimated for 1.5 m soil depth, whereas the other soil parameters refer to samples from the plough horizon (0.3 m). Due to the pronounced spatial variation of the geological layering within the test field soil, the AWC is only slightly 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 on this experimental field.

N_t and SOC were closely correlated, but did not show considerable spatial variation within the field (CV 7.8 and 6.4%, resp.). Regarding texture, sand was more variable (CV 19%) than silt and clay (CV 4.7 and 5.9%, respectively). The plant available amounts of P, K and Mg were heterogeneously distributed with CVs > 14% (Table 2).

Variability of weed distribution during the long-term survey

The weed distribution in the test field revealed considerable heterogeneity regarding the spatial patterns of the different species as well as their density. Consistently occurring and dominant weed species were *Chenopodium album* (L.), *Polygonum aviculare* (L.), *Viola*

Table 1 Statistical parameters of mid-infrared spectroscopy-partial least squares regression (MIRS-PLSR)

Soil property	Full cross-validation			Test-set validation (30%)		
	R^2	$RMSE_{CV}^a$	RPD^b	R^2	$RMSE_p^c$	RPD^b
Clay (g kg^{-1})	0.98	2.30	6.64	0.97	2.70	5.65
Silt (g kg^{-1})	0.94	17.5	3.99	0.93	21.1	3.81
Sand (g kg^{-1})	0.99	9.51	8.31	0.98	11.5	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
pH- CaCl_2	0.70	0.17	1.83	0.63	0.21	1.73

Predictions were conducted for mean contents of clay, silt, sand, soil organic carbon (SOC) and total nitrogen (Nt) in the topsoil (0–0.3 m depth)

^aRoot mean squared error of cross validation

^bRatio of performance to deviation

^cRoot mean square error of prediction

Table 2 Statistical parameters of the observed soil properties (n = 429)

Soil properties	Min	Max	Mean	Median	SD	CV (%) ^a
Clay (g kg ⁻¹) ^a	120	186	156	157	9.2	5.9
Silt (g kg ⁻¹) ^a	501	714	653	662	31	4.7
Sand (g kg ⁻¹) ^a	133	331	194	183	37	19
AWC (mm) ^b	57	426	207	206	74	36
Nt (g kg ⁻¹) ^a	0.85	1.31	1.03	1.03	0.08	7.8
SOC (g kg ⁻¹) ^a	9.78	15.2	11.7	11.7	0.75	6.4
P-CAL (mg kg ⁻¹) ^c	47	129	74	74	10	14
K-CAL (mg kg ⁻¹) ^c	79	252	115	116	19	17
Mg-CaCl ₂ (mg kg ⁻¹) ^c	13	62	47	48	11	23
pH-CaCl ₂ ^a	6.36	7.22	6.82	6.84	0.12	1.8

Data refer to the plough horizon (except AWC that was estimated for 1.5 m depth)

SD standard deviation, CV coefficient of variation

^aMIRS prediction. Please note that for the correlations to weed patterns only MIRS data were used

^bAWC = available water capacity derived from EC_a, summarised over 1.5 m soil depth

^cConventional chemical extraction

arvensis (Murray) and grass weeds, the latter dominated with about 80% by *Alopecurus myosuroides* (Huds.) (Fig. 1). Hence, these four species were chosen for data analyses. 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 per m², while the mean weed density of the other three species was about 11 plants per m² (Fig. 1). Weed patches with up to about 280 plants per m² were found in single years for each species except for *C. album* with a maximum weed density of 155 plants per m².

Abundance 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 (Table 3). The large coefficients of determination ($R^2 = 0.96$ to 0.98) indicated pronounced heterogeneity of weed patch occurrence. Significant positive autocorrelations ($p < 0.001$) were found for all observed GWR models. Positive Moran's I values (0.11 to 0.22) and large positive Z values (6.09 to 16.53) indicate that weed species abundance between 1998 and 2008 was spatially correlated.

Site-specific preferences of the individual species at the test site are displayed as the mean abundance during the whole study period in Fig. 1c–f. Obviously, *C. album* and *V. arvensis* were competitive on opposing site conditions (Fig. 1c, e). The highest densities of *C. album* were observed in the north of the test field, while *V. arvensis* was predominantly found in the southern part of the surveyed area. Note that the entire field had been uniformly managed with respect to crop rotation and agronomic measures for decades. A former study on site-specific weed control had no effect on long-term weed abundance (Dicke and Kühbauch 2006). The opposite gradients of both species were only partially correlated with the AWC (Fig. 1b). Yet, *P. aviculare* and grass weeds also revealed opposite gradients, but with patterns similar to that of AWC (Fig. 1b, d, f). While *P. aviculare* seemed to be more competitive in areas with low to medium AWC (< 140 mm), grass

Fig. 1 Spatial patterns in the test field: **a** aerial image (orthophoto) from August 2008 including intersecting points of the sampling grid; crop: maize; **b** available water capacity (AWC) including intersecting points of the sampling grid; mean abundance (plants per m²) of the whole study period (1998–2008) for **c** *Chenopodium album*, **d** *Polygonum aviculare*, **e** *Viola arvensis* and **f** grass weeds

Table 3 Statistical test results from geographically weighted regression (GWR) and Global Moran's I of weed species abundance between various years within the long-term survey

	<i>C. album</i>	<i>P. aviculare</i>	<i>V. arvensis</i>	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

weeds favoured sites with extremely high AWC (> 250 mm). Furthermore, spatial variation of AWC obviously coincided with patterns of grain maize biomass as visible in the aerial image (Fig. 1a, b). On the same field, Timmermann et al. (2003), Mertens et al. (2008)

and Sun et al. (2011) consistently found similar patterns between soil properties and maize growth and yield, respectively. Hence, the soil water supply directly affected interaction and competitiveness of weeds and crops.

Variability of weed distribution as affected by environmental parameters

The density of weeds within and between individual field crops is displayed in Fig. 2. All weeds under study revealed the highest densities in the summer annual row crops (grain maize and sugar beet), with the exception of *V. arvensis*, whose density did not differ between sugar beet and winter cereals. Weed populations in grain maize were clearly dominated by *C. album*, while grass weeds significantly dominated in sugar beet. In winter cereals, *V. arvensis* was the most frequently occurring species. Interactions between crop and weeds are well known and related to the characteristics of the specific crop such as sowing period, crop stand development, etc. (Kaur et al. 2018).

Variations in weed density and composition were also found between particular years (data not shown). Such year-dependant differences can be caused by many parameters. Beside crop rotation, soil tillage in particular, affects weed emergence (Cardina et al. 2002; Sosnoskie et al. 2006). Yet, this factor was negligible here, because tillage remained consistent during the whole survey. However, temperature and rainfall also affect weed population dynamics (Cousens and Mortimer 1995; Kobusch 2003). Furthermore, weed density, competition pressure and thus inter-relations between weeds and crops additionally modify species composition (Cousens and Mortimer 1995; Ritter and Gerhards 2008).

To elucidate these multifactorial influences, RDA was carried out on the explanatory variables year, crop and diverse soil properties. These environmental variables together had significant effects on the weed data variability. Table 4 shows results for four different

Fig. 2 Averaged weed density of individual weed 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 the standard error

analyses (a1–a4) of the explanatory power of years, field crops and soil properties. It has to be noted that RDA expresses the summed effect of these variables on weeds in total and does not aim to identify their individual effects on distinct species. As well, no isolated analysis of single environmental factors (such as distinct soil properties) was conducted here. Influences of single soil properties are described in the next section. However, this approach takes the complexity of weed occurrence into account (see above). The effect of year, crop and soil properties together explained 47% (analysis a1, all canonical axes) of weed variability (i.e., species composition and abundance) for all years of the long-term survey, while the first canonical axis explained just 20.8% of weed data variability (Table 4, analysis a1, axis 1). Considering all canonical axes for each explanatory variable separately, the factor years explained the highest proportion of weed variability (36.9%, analysis a2), while various field crops revealed the lowest explanatory power (11.2%, analysis a3, Table 4). For the year-dependent analysis, weed data of all years of the long-term survey were separated, while for the field crop-dependent analysis only weed data of the years with different field crops were selected. Averaged weed data of all years together 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 composition and abundance (analysis a4). Taking only 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% (Table 4).

Certainly, crop- and year-dependent differences were responsible for some temporal variation in weed species abundance in the present data set. However, neither differences of years nor the effect of different field crops could solely explain the spatial variability of weed species. Thus, the further focus was to elucidate in detail the effect of single soil properties, which explained 23.7% of weed variability anyhow (Table 4).

Effects of various soil properties on weed distribution

Soil texture, AWC and SOC were regarded as stable over time in view of the consistent tillage. With regard to texture and SOC, this is in accordance with data from Heisel et al. (1999). Further, uniform liming and fertilisation of the field led to the assumption of stable patterns of pH values and plant available nutrients over the survey period; this assumption was confirmed by the long-term experience of the farm manager (H. Hüging, *pers. comm.*).

Table 4 Results and statistical evaluation of redundancy analyses (RDA) for the relation between weed species abundance and all environmental parameters together (a1) and separated in relation to years, field crops and soil properties (a2–a4), respectively

No.	Explanatory variable	First canonical axis			All canonical axes		
		%	<i>F</i>	<i>p</i>	%	<i>F</i>	<i>p</i>
a1	Year, field crop, soil	20.8	1005.6	0.001	47.0	161.9	0.001
a2	Year	18.3	863.3	0.001	36.9	281.6	0.001
a3	Field crop	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

In consequence, averaged weed data from all years studied were used for multivariate analyses of soil properties.

The soil properties under study explained in total 30.7% of the variability in weed species data when the environmental variables year and crop were omitted and only the diverse soil properties under study were subjected to RDA (Table 5, analysis a5, first canonical axis). During automatic forward selection of environmental variables, P-CAL and K-CAL were omitted with respect to their minor influence on weeds (not shown). The remaining seven soil parameters were identified as important: clay, silt, sand, AWC, SOC, pH and Mg-CaCl₂. All weed species were more or less clearly positively or negatively correlated to different texture parameters, AWC and soil pH (Fig. 3). The long arrow for SOC also indicated a strong, but more or less non-directional effect on weed species.

Further division of the selected explanatory variables indicate the explanatory power of the individual soil properties. In a statistical sense, the most decisive soil property affecting weed species composition was AWC (estimated for 1.5 m depth), which explained 17.4% of weed data variability (analysis a9), followed by clay and sand contents in the plough horizon. Additionally, SOC and silt contents also possessed considerable explanatory power. The combination of these five most important soil properties explained a remarkable 28.2% of weed species variability (analysis a13). Considering all canonical axes, 30.9% of weed species composition could be explained by soil texture and SOC content in the plough horizon and AWC of the soil profile (analysis a14, Table 5). Note that the statistically proved coincidence between weeds and soil does not necessarily point to a cause-effect relationship.

Figure 3 visualises the result of analysis a13 (Table 5). The abundance of *C. album* was positively correlated with sand content and AWC, but negatively with clay content. In contrast, *P. aviculare* was positively correlated with the clay content and negatively correlated to AWC. Clay and silt content positively affected *V. arvensis*, which, in turn, was negatively correlated with the sand content. Grass weeds were positively correlated with AWC. The non-directional effect of SOC on all observed weed species (Fig. 3) points to the high complexity of soil properties, their inter-relationships, as well as their complex effects on weed growth conditions.

Table 5 Results and statistical evaluation of redundancy analyses (RDA) for weed species abundance in relation to various soil properties of the plough horizon (except AWC: estimated for 1.5 m depth)

No.	Explanatory variable	First canonical axis			All canonical axes		
		%	F	p	%	F	p
a5	Clay, silt, sand, AWC, SOC, pH-CaCl ₂ , Mg-CaCl ₂	30.7	186.9	0.001	34.6	31.9	0.001
a6	Clay	13.2	64.9	0.001	–	–	–
a7	Silt	5.3	23.9	0.001	–	–	–
a8	Sand	12.4	60.3	0.001	–	–	–
a9	AWC	17.4	89.8	0.001	–	–	–
a10	SOC	8.4	39.1	0.001	–	–	–
a11	pH-CaCl ₂	3.6	16.1	0.001	–	–	–
a12	Mg-CaCl ₂	3.6	15.7	0.001	–	–	–
a13	Clay, silt, sand, AWC, SOC	28.2	166.3	0.001	30.9	37.8	0.001

^aAWC = available water capacity, summarised over 1.5 m soil depth

Fig. 3 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*

The apparent contradiction between texture parameters in the topsoil and AWC can be explained by the two geological layers in the soil as described above. The AWC as derived from EC_a for 1.5 m soil depth generally characterized the length of moist soil conditions and might be most important during later phases of the vegetation period. Soil texture in the plough horizon might be more important in, e.g., early spring when sandy areas warm up more quickly. In consequence, both parameters, although interacting, have explanatory power and must be interpreted separately for elucidating weed occurrence.

Similarly, the influence of topsoil texture and SOC (Fig. 3) cannot be interpreted separately, because both are key parameters that control other parameters such as soil porosity, aggregate stability, soil respiration or nutrient status in a complex way. Consequently, overall growth conditions of weeds and crops are affected.

Concerning the weeds under study, *C. album* as a thermophile weed is relatively resistant to drought stress (Bruckner-Pertl et al. 2001) and therefore may benefit from a rather high competitiveness in a sandy soil. Andreasen et al. (1991) observed a negative correlation between *C. album* and clay content. These findings are in line with the results presented. The abundance of *P. aviculare* and *V. arvensis* was positively affected by topsoil clay and silt content in this study, respectively (Fig. 3). In contrast, Andreasen et al. (1991), Walter et al. (2002) and Mehrrens (2005) related *P. aviculare* and *V. arvensis* abundance with lower clay or higher sand contents. According to Nordmeyer and Niemann (1992), also *A. myosuroides*, the main grass weed in the test field of the present study, was associated with high clay contents which was also not in line with the results here. These different results indicate once more the complexity of relations between weeds and soil.

Perspective: weed management maps for site-specific weed management

Weed maps displaying the spatial weed distribution and density for the subsequent patch spraying of herbicides can be frequently found in the literature (e.g. Dicke et al. 2004; Gutjahr et al. 2008; Kroulik et al. 2008; Andujar et al. 2017). Gerhards and Oebel (2006) and Weis et al. (2008) used weed maps to derive decision algorithms for site-specific weed management and patch spraying. These approaches were mostly based on automated weed detection, i.e., direct weed information. Yet, the effect of soil heterogeneity has not yet been taken into account, even if its effect on weed variability is evident. Nevertheless, weed management maps may help to save herbicides or to fulfil regulatory restrictions and are, consequently, potentially helpful within the scope of precision crop protection (Patzold et al. 2008). Thus, management maps were created with regard to the relation between weeds and soil as exemplars.

In view of the spatial coincidence between (i) sand and *C. album* as well as *V. arvensis*, and (ii) AWC and *P. aviculare* and grass weeds, two related soil maps were generated. The displayed sand content was divided into two areas with low (< 18%, area 1) and high (> 18%, area 2) sand content (Fig. 4a). The AWC was visualised in three levels with low to medium (< 140 mm, area 1), high (140–200 mm, area 2) and extremely high (> 200 mm, area 3),

Fig. 4 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 (0–0.3 m depth), **b** map of the available water capacity (AWC) in the main root zone (0–1.5 m depth), **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)

area 3) AWC (Fig. 4b). The averaged abundance of the observed weeds within the different areas and with respect to the economic weed thresholds are shown in Figs. 4c, d. The economic weed threshold was taken from Dicke et al. (2004), who suggested 10 plants per m^{-2} for dicots and 6 plants per m^{-2} for monocots. While *V. arvensis* exceeds the economic weed threshold at low sand contents (area 1 of the sand content map), *C. album* does not reach it, which is vice versa in area 2 (high sand content, Fig. 4c). *P. aviculare* exceeds 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. 4d).

Weed thresholds are target values which help farmers to decide if herbicide application is economic or not. Soil maps as displayed in this study can thus serve as supporting information for weed management planning. Site-specific application of herbicides with respect to soil texture zones and the SOC content show economic benefits, and can reduce the environmental burden, or allow fulfilling registration requirements (Walter et al. 2002; Patzold et al. 2008). In European countries, some herbicidally-active ingredients are subject to application restrictions with respect to soil texture and/or SOC content (e.g., for Germany: BVL 2018; for France: Arvalis 2019). Herbicide selection and dosage can be adapted to expected weed occurrence and thresholds on the one hand and soil-related needs and restrictions on the other hand.

Patch-spraying after automated weed counting (e.g. by image analyses) is based on more direct information and can potentially reduce herbicide use (Gerhards et al. 2005; Weis et al. 2008; Laursen et al. 2016). However, weed management maps that are based on and account for spatially heterogeneous soil properties are potentially useful, e.g. for herbicide planning. Further, the results of RDA and the displayed maps contribute to a better understanding of site-specific inter-relations between weeds and soil properties. Up to now, the results presented originate from a case study on a 4 ha field and apply to this specific site and crop rotation. For a more general understanding of soil-weed-crop interactions, more research is needed. However, soil sensing technologies can contribute, because they allow data acquisition at high spatial resolution and low cost. Technical progress will allow capture of more soil properties or to enhance sensor performance. For example, infrared spectroscopy in the visible and near-infrared range (Vis-NIRS) was successfully used to measure SOC content on-the-go (Rodionov et al. 2014), and gamma spectrometry served to determine topsoil texture directly in the field (Heggemann et al. 2017). Mobile MIR application for soil analyses will probably be available in future, but has not yet been tested under field conditions (Soriano-Disla et al. 2017).

Perspectives for future research

The following thoughts should be considered in future research:

- (i) Existing knowledge on weed biology and crop interactions could be extended by soil effects. Yet, the indispensable large data density is only achievable through sensor application. This case study reveals that it is worth conducting further studies in this respect.
- (ii) Sampling strategies can be focused. Weed counting as well as soil sampling can be reduced and targeted with respect to the stability of weed patches and soil properties such as SOC content and texture over time. Preferable weed survey locations can be identified on the basis of a sensor-based soil survey.

- (iii) Optimization strategies for herbicide application should be developed in a site-specific way. Due to the effect of soil properties on herbicide efficacy and leaching, variable herbicide dosages with respect to soil textural zones and SOC distribution should be tested.
- (iv) The outcome of other highly resolved soil sensing data should be evaluated with respect to weed occurrence.

Conclusions

Within the 9-year survey, a clear incidence of weed patches and their relations to soil properties became obvious. Besides field crops and annual weather conditions, soil heterogeneity also significantly affected weed species abundance and distribution. The combination of soil sensing technologies and multi-variate RDA allowed detection of a surprisingly strong effect of different soil properties on weed variability because large observation numbers could be evaluated. In this case-study, soil texture, AWC and SOC content, altogether determining plant available water and nutrient contents, mainly affected weed species variability. RDA accounts for the complex interactions between various soil properties; further, impacts of these interacting soil properties on different weed species are considered. So RDA elucidates relationships in a multi-dimensional space, which is not possible with a one-dimensional data analysis. It is therefore suggested that multivariate analysis such as RDA should be more frequently used when interdisciplinary questions are asked.

Weed maps based on spatially resolved soil data can potentially be integrated into weed management planning in terms of, e.g. estimating herbicide requisition or fulfilling application limitations.

Soil properties at the required data density can only be detected with non- or minimally-invasive technologies if interactions with weed occurrence are to be elucidated; this explains why related studies are scarce up to now. The approach presented here is a step towards closing that gap: utilizing MIRS allows for examination of much larger sample numbers than conventional analyses, and multivariate statistics require such a broad data basis. The study was only possible by combining these methods.

Acknowledgements This study has been conducted within the Research Training Group 722 ‘Information Technologies for Precision Crop Protection’. Funding by the German Research Foundation (DFG) is gratefully acknowledged. Jürgen Schellberg provided valuable help in conducting the statistical analyses. The authors are thankful to the staff of INRES–Soil Science and Soil Ecology for their assistance in the laboratory.

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

References

- Ahmad, Z., Khan, S. M., Abd Allah, E. F., Alqarawi, A. A., & Hashem, A. (2016). Weed species composition and distribution pattern in the maize crop under the influence of edaphic factors and farming practices: A case study from Mardan, Pakistan. *Saudi Journal of Biological Sciences*, 23, 741–748.
- Andreasen, C., Streibig, J. C., & Haas, H. (1991). Soil properties affecting the distribution of 37 weed species in Danish fields. *Weed Research*, 31, 181–187.

- Andujar, D., Rodriguez, X., Rueda-Ayala, V., San Martin, C., Ribeiro, A., Fernandez-Quintanilla, C., et al. (2017). A geometrical model to predict the spatial expansion of sorghum halepense in maize fields. *Gesunde Pflanzen*, 69, 73–81.
- Arvalis (2019). Arvalis—Institut du vegetal: Choisir et décider—préconisations régionales campagne 2019-2020 (Select and decide—regional recommendations campaign 2019-2020). choisir_1_bth_desherbage_varietes_interventions_automne_bfc_alsace_5796738637495490328.pdf. Retrieved 2 September, 2019 from <https://www.arvalis-infos.fr/ble-tendre-bien-demarrer-la-campagne-2019/2020-@/view-19261-arvarticle.html>.
- Bärberi, P., & Lo Cascio, B. (2001). Long-term tillage and crop rotation effects on weed seedbank size and composition. *Weed Research*, 41, 325–340.
- Bornemann, L., Welp, G., Brodowski, S., Rodionov, A., & Amelung, W. (2008). Rapid assessment of black carbon in soil organic matter using mid-infrared spectroscopy. *Organic Geochemistry*, 39, 1537–1544.
- Bruckner-Pertl, C., Hain, E., & Langer, C. (2001). *Grundwissen Unkräuter auf Kulturland (Basic knowledge weeds on cultivated land)*. Cologne, Germany: Bildungsverlag EINS.
- BVL (2018). Bundesamt für Verbraucherschutz und Lebensmittelsicherheit (German Federal Office for Consumer Protection and Food Safety): *Pflanzenschutzmittel-Verzeichnis Teil 1* (Register of plant protection products 2018 Part 1), psm_verz_1.pdf. Retrieved 2 September, 2019 from https://www.bvl.bund.de/DE/04_Pflanzenschutzmittel/01_Aufgaben/02_ZulassungPSM/01_ZugelPSM/05_Verzeichni s/psm_ZugelPSM_Verzeichnis_node.html.
- Cardina, J., Herms, C. P., & Doohan, G. J. (2002). Crop rotation and tillage system effects on weed seedbanks. *Weed Science*, 50, 448–460.
- Charlton, M. E. & Fotheringham, A. S. (2009). *Geographically weighted regression—A tutorial on using GWR in ArcGIS 9.3*. National Centre for Geocomputation, National University of Ireland Maynooth. Retrieved 2 September, 2019 from https://www.geos.ed.ac.uk/~gisteac/fspat/gwr/gwr_arcgis/GWR_Tutorial.pdf.
- Chhokar, R. S., Sharma, R. K., & Sharma, I. (2012). Weed management strategies in wheat—A review. *Journal of Wheat Research*, 4, 1–21.
- Christensen, S., Heisel, T., Walter, A. M., & Graglia, E. (2003). A decision algorithm for patch spraying. *Weed Research*, 43, 276–284.
- Corwin, D. I., & Lesch, S. W. (2003). Application of soil electrical conductivity to precision agriculture: Theory, principles, and guidelines. *Agronomy Journal*, 95, 455–471.
- Cousens, R., & Mortimer, M. (1995). *Dynamics of weed populations*. Cambridge, UK: Cambridge University Press.
- Dicke, D., Fries, A., Gerhards, R. (2004). Ermittlung von Schadschwellen für die teilschlagspezifische Unkrautbekämpfung im Braugerstenanbau (Determination of weed thresholds for site-specific weed control in malting barley). *Journal of Plant Diseases and Protection*, Special Issue XIX, 413–421.
- Dicke, D., Gerhards, R., Büchse, A., & Hurle, K. (2007). Modeling spatial and temporal dynamics of *Chenopodium album* L. under the influence of site-specific weed control. *Crop Protection*, 26, 206–211.
- Dicke, D. & Kühbauch, W. (2006). Temporal dynamics of weed populations in arable fields using long-term site-specific weed control. In *Proceedings of the 15th Australian weeds conference* (pp. 375–378). Torrens Park, South Australia: Weed Management Society of South Australia Inc.
- Dieleman, J. A., Mortensen, D. A., & Martin, A. R. (1999). Influence of velvetleaf (*Abutilon theophrasti*) and common sunflower (*Helianthus annuus*) density variation on weed management outcomes. *Weed Science*, 47, 81–89.
- Ferreira, A. D., Freitas, D. M., da Silva, G. G., Pistori, H., & Folhes, M. T. (2017). Weed detection in soybean crops using ConvNets. *Computers and Electronics in Agriculture*, 143, 314–324.
- Franco, C., Pedersen, S. M., Papaharalamos, H., & Ørum, J. E. (2017). The value of precision for image-based decision support in weed management. *Precision Agriculture*, 18, 366–382.
- Gaston, L. A., Locke, M. A., Zablotowicz, R. M., & Reddy, K. N. (2001). Spatial variability of soil properties and weed populations in the Mississippi Delta. *Soil Science Society of America Journal*, 65, 449–459.
- Gerhards, R., Bezhin, K., & Santel, H. J. (2017). Sugar beet yield loss predicted by relative weed cover, weed biomass and weed density. *Plant Protection Science*, 53, 118–125.
- Gerhards, R., & Christensen, S. (2003). Real-time weed detection, decision making and patch spraying in maize, sugarbeet, winter wheat and winter barley. *Weed Research*, 43, 385–392.
- Gerhards, R., Dicke, D., & Oebel, H. (2005). Testing and analysing decision rules for site-specific weed control in malt barley (*Hordeum vulgare* L.) using a geographic information system. *Journal of Plant Diseases and Protection*, 112, 447–456.

- Gerhards, R., & Oebel, H. (2006). Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. *Weed Research*, 46, 185–193.
- Gooley, J., Huang, J., Pagé, D., & Triantafyllis, J. (2014). Digital soil mapping of available water content using proximal and remotely sensed data. *Soil Use and Management*, 30, 139–151.
- Gray, C. J., Shaw, D. R., Gerard, P. D., & Bruce, L. M. (2008). Utility of multispectral imagery for soybean and weed species differentiation. *Weed Technology*, 22, 713–718.
- Gutjahr, C., Weis, M., Sökefeld, M., Ritter, C., Möhring, J., Büchse, A., et al. (2008). Erarbeitung von Entscheidungsalgorithmien für die teilflächenspezifische Unkrautbekämpfung (Development of decision-making algorithms for site-specific weed control). *Journal of Plant Diseases and Protection*, Special Issue XXI, 143–148.
- Hald, A. B. (1999). The impact of changing the season in which cereals are sown on the diversity of the weed flora in rotational fields in Denmark. *Journal of Applied Ecology*, 36, 24–32.
- Heggenmann, T., Welp, G., Amelung, W., Angst, G., Franz, S. O., Koszinski, S., et al. (2017). Proximal gamma-ray spectrometry for site-independent in situ prediction of soil texture on ten heterogeneous fields in Germany using support vector machines. *Soil and Tillage Research*, 168, 99–109.
- Heisel, T., Ersbøll, A. K., & Andreasen, C. (1999). Weed mapping with co-kriging using soil properties. *Precision Agriculture*, 1, 39–52.
- Hejzman, M., Češková, M., Schellberg, J., & Pätzold, S. (2010). The Rengen grassland experiment: Effect of soil chemical properties on biomass production, plant species composition and species richness. *Folia Geobotanica*, 45, 125–142.
- Hyvönen, T., Glemnitz, M., Radics, L., & Hoffmann, J. (2010). Impact of climate and land use type on the distribution of Finnish causal arable weeds in Europe. *Weed Research*, 51, 201–208.
- ISO. (2002). *Soil quality—Determination of particle size distribution in mineral soil material—Method by sieving and sedimentation (ISO 11277)*. Vernier, Switzerland: International Organization for Standardization.
- IUSS. (2015). IUSS Working Group WRB, World reference base for soil resources 2014, update 2015. *World Soil Resources Reports* 106. Rome, Italy: FAO.
- Jacobi, J., Backes, M., Kühbauch, W. & Plümer, L. (2006). Identifikation von Unkräutern in Zuckerrüben anhand spektraler Reflexionsunterschiede in Fernerkundungsaufnahmen (Identification of weeds in remote-sensed images on the basis of differences in spectral reflectance). *Journal of Plant Diseases and Protection*, Special Issue XX, 241–248.
- Kaur, S., Kaur, R., & Chauhan, B. S. (2018). Understanding crop-weed-fertilizer-water interactions and their implications for weed management in agricultural systems. *Crop Protection*, 103, 65–72.
- Kobusch, H. (2003). *Unkrautbekämpfung in Zuckerrüben—Ermittlung der Kritischen Periode (Weed control in sugar beets—identification of the critical period)*. Dissertation, University of Hohenheim, Germany.
- Korres, N. E., Norsworthy, J. K., Brye, K. R., Skinner, V., Jr., & Mauromoustakos, A. (2017). Relationships between soil properties and the occurrence of the most agronomically important weed species in the field margins of eastern Arkansas—Implications for weed management in field margins. *Weed Research*, 57, 159–171.
- Kroulik, M., Slejska, A., Mirma, M., Prosek, V., Kumhalova, J., Kokoskova, D. et al. (2008). Mapping of *Cirsium arvense* infestation and site specific herbicide application. *Journal of Plant Diseases and Protection*, Special Issue XXI, 171–176.
- Kuang, B., Mahmood, H. S., Quraishi, M. Z., Hoogmoed, W. B., Mouazen, A. M., & van Henten, E. J. (2012). Sensing soil properties in the laboratory, in situ, and on-line. A review. *Advances in Agronomy*, 114, 155–223.
- Kulkarni, S. S., Dosdall, L. M., Spence, J. R., & Willenborg, C. J. (2017). Field density and distribution of weeds are associated with spatial dynamics of omnivorous ground beetles (Coleoptera: Carabidae). *Agriculture, Ecosystems & Environment*, 236, 134–141.
- Laursen, M. S., Jorgensen, R. N., Midtby, H. S., Jensen, K., Christiansen, M. P., Giselsson, T. M., et al. (2016). Dicotyledon weed quantification algorithm for selective herbicide application in maize crops. *Sensors*, 16, 1848.
- Lepš, J., & Šmilauer, P. (2003). *Multivariate analysis of ecological data using CANOCO*. Cambridge, UK: Cambridge University Press.
- Liu, Y., Guo, L., Jiang, Q., Zhang, H., & Chen, Y. (2015). Comparing geospatial techniques to predict SOC stocks. *Soil & Tillage Research*, 148, 46–58.
- Long, R. L., Kranner, I., Panetta, F. D., Birtic, S., Adkins, S. W., & Steadman, K. J. (2011). Wet-dry cycling extends seed persistence by re-instating antioxidant capacity. *Plant and Soil*, 338, 511–519.

- Malmstrom, C. M., Butterfield, H. S., Planck, L., Long, C. W., & Eviner, V. T. (2017). Novel fine-scale aerial mapping approach quantifies grassland weed cover dynamics and response to management. *PLoS ONE*, 12, e0181665.
- Marshall, E. J. P., Brown, V. K., Boatman, N. D., Lutman, P. J. W., Squire, G. R., & Ward, L. K. (2003). The role of weeds in supporting biological diversity within crop fields. *Weed Research*, 43, 77–89.
- Mehrtens, J. (2005). *Räumliche und zeitliche Verteilung von Unkräutern in Mais (Spatial and temporal distribution of weeds in maize)*. Dissertation, University of Hohenheim, Germany.
- Mertens, F. M., Pätzold, S., & Welp, G. (2008). Spatial heterogeneity of soil properties and its mapping with apparent electrical conductivity. *Journal of Plant Nutrition and Soil Science*, 171, 146–154.
- Metcalfe, H., Milne, A. E., Webster, R., Lark, R. M., Murdoch, A. J., & Storkey, J. (2016). Designing a sampling scheme to reveal correlations between weeds and soil properties at multiple spatial scales. *Weed Research*, 56, 1–13.
- Mhlanga, B., Chauhan, B. S., & Thierfelder, C. (2016). Weed management in maize using crop competition: A review. *Crop Protection*, 88, 28–36.
- Nordmeyer, H., & Häusler, A. (2004). Einfluss von Bodeneigenschaften auf die Segetalflora von Ackerflächen (Impact of soil properties on weed distribution within agricultural fields). *Journal of Plant Nutrition and Soil Science*, 167, 328–336.
- Nordmeyer, H. & Niemann, P. (1992). Möglichkeiten der gezielten Teilflächenbehandlung mit Herbiziden auf der Grundlage von Unkrautverteilung und Bodenvariabilität (Chances for site-specific herbicide application based on weed distribution maps and soil variability). *Journal of Plant Diseases and Protection*, Special Issue XIII, 539–547.
- Oerke, E.-C., & Dehne, H.-W. (2004). Safeguarding production—Losses in major crops and the role of crop protection. *Crop Protection*, 23, 275–285.
- Pantazi, X.-E., Moshou, D., & Bravo, C. (2016). Active learning system for weed species recognition based on hyperspectral sensing. *Biosystems Engineering*, 146, 193–202.
- Pätzold, S., Mertens, F. M., Bornemann, L., Koleczek, B., Franke, J., Feilhauer, J., et al. (2008). Soil heterogeneity at the field scale: A challenge for precision crop protection. *Precision Agriculture*, 9, 367–390.
- Pätzold, S. & Welp, G. (2009). Exkursion H2—Bodenheterogenität auf der Feldskala: eine Herausforderung für den Präzisionslandbau (Excursion H2—Soil heterogeneity at field scale: a challenge for precision farming). *Mitteilungen der Deutschen Bodenkundlichen Gesellschaft* 112, 179–188. Bd112.pdf. Retrieved 2 September, 2019 from <https://www.dbges.de/de/publikationen/mitteilung-en-der-dbg-und-exkursionsfuehrer>.
- Perry, E. M., Dezzani, R. J., Seavert, C. F., & Pierce, F. J. (2010). Spatial variation in tree characteristics and yield in a pear orchard. *Precision Agriculture*, 11, 42–60.
- Pinke, G., Pál, R., Botta-Dukát, Z., & Chytrý, M. (2009). Weed vegetation and its conservation value in three management systems of Hungarian winter cereals on base-rich soils. *Weed Research*, 49, 544–551.
- Rew, L. J., & Cousens, R. D. (2001). Spatial distribution of weeds in arable crops: Are current sampling and analytical methods appropriate? *Weed Research*, 41, 1–18.
- Ritter, C., Dicke, D., Weis, M., Oebel, H., Piepho, H. P., Büchse, A., et al. (2008). An on-farm approach to quantify yield variation and to derive decision rules for site-specific weed management. *Precision Agriculture*, 9, 133–146.
- Ritter, C. & Gerhards, R. (2008). Population dynamics of *Galium aparine* L. and *Alopecurus myosuroides* Huds. under the influence of site-specific weed management. *Journal of Plant Diseases and Protection*, Special Issue XXI, 209–214.
- Rodionov, A., Welp, G., Damerow, L., Berg, T., Amelung, W., & Pätzold, S. (2014). Towards on-the-go field assessment of soil organic carbon using Vis–NIR diffuse reflectance spectroscopy: Developing and testing a novel tractor-driven measuring chamber. *Soil & Tillage Research*, 145, 93–102.
- Schmittmann, O., & Schulze Lammers, P. (2017). A true-color sensor and suitable evaluation algorithm for plant recognition. *Sensors*, 17(8), 1823.
- Soriano-Disla, J. M., Janik, L. J., Allen, D. J., & McLaughlin, M. J. (2017). Evaluation of the performance of portable visible-infrared instruments for the prediction of soil properties. *Biosystems Engineering*, 161, 24–36.
- Sosnoskie, L. M., Herms, C. P., & Cardina, J. (2006). Weed seedbank community composition in a 35-yr-old tillage and rotation experiment. *Weed Science*, 54, 263–273.
- Squire, G. R., Rodger, S., & Wright, G. (2000). Community-scale seedbank response to less intense rotation and reduced herbicide input at three sites. *Annals of Applied Biology*, 136, 47–57.

- Šrek, P., Hejzman, M., & Kunzová, E. (2010). Multivariate analysis of relationships between potato (*Solanum tuberosum* L.) yield, amount of applied elements, their concentrations in tubers and uptake in a long-term fertilizer experiment. *Field Crops Research*, 118, 183–193.
- Sun, Y., Druceker, H., Hartung, E., Hueging, H., Cheng, Q., Zeng, Q., et al. (2011). Map-based investigation of soil physical conditions and crop yield using diverse sensor techniques. *Soil & Tillage Research*, 112, 149–158.
- ter Braak, C. J. F., & Prentice, I. C. (1988). A theory of gradient analysis. *Advances in Ecological Research*, 18, 271–317.
- ter Braak, C. J. F., & Šmilauer, P. (2002). *CANOCO reference manual and CanoDraw for Windows user's guide: Software for canonical community ordination (version 4.5)*. Ithaca, NY, USA: Microcomputer Power.
- Timmermann, C., Gerhards, R., & Kühbauch, W. (2003). Analyse der Ertrags- und Unkrautkartierung in Ackerschlügen mit einem Geo-Information-System (GIS) (Analysis of the yield and weed distribution in arable fields in a Geo Information System (GIS)). *Journal of Agronomy and Crop Science*, 188, 34–42.
- Tu, J., & Xia, Z.-G. (2008). Examining spatially varying relationships between land use and water quality using geographically weighted regression. I: Model design and evaluation. *Science of the Total Environment*, 407, 358–378.
- van Evert, F. K., Fountas, S., Jakovetic, D., Crnojevic, V., Travlos, I., & Kempenaar, C. (2017). Big data for weed control and crop protection. *Weed Research*, 57, 218–233.
- Viscarra Rossel, R. A., Walvoort, D. J. J., McBratney, A. B., Janik, L. J., & Skjemstad, J. O. (2006). Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma*, 131, 59–75.
- Walter, A. M., Christensen, S., & Simmelsgaard, S. E. (2002). Spatial correlation between weed species densities and soil properties. *Weed Research*, 42, 26–38.
- Webster, R. (2010). Weeds, worms and geostatistics. In M. A. Oliver (Ed.), *Geostatistical applications for precision agriculture* (pp. 221–241). Dordrecht, The Netherlands: Science+Business Media B.V.
- Weis, M., Gutjahr, C., Rueda Ayala, V., Gerhards, R., Ritter, C., & Schölderle, F. (2008). Precision farming for weed management: Techniques. *Gesunde Pflanzen*, 60, 171–181.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.