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Arable Weeds—More Than Just Competitors? Including Weed Functional Traits into Site-Specific Weed Management

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Abstract

In an agricultural context, weeds are often perceived as harmful because they compete with crops for light, water, and nutrients. However, weeds can also provide valuable ecosystem services, including support for pollinators, natural enemies of pest species, and birds. This thesis presents a concept for integrating weed functional traits that describe the adverse effects of weed species on crop productivity (disservice potential) and those that provide ecosystem services (service potential) into spatially explicit weed distribution maps. The information gained is used for site-specific weed management (SSWM) decision-making. In SSWM, weed control treatments are targeted at specific weed plants or areas in the field, allowing for weed-specific recommendations and reducing herbicide use.

The first challenge of SSWM involves adequately mapping the spatial distributions of weed species without conducting a field-wide weed assessment. One possible approach for field-wide mapping is to assess weed densities using a grid-based sampling design, followed by estimating densities between the georeferenced sampling points through spatial interpolation. As part of this thesis, various manual weed sampling designs were tested to determine the optimal combination of grid sampling arrangement and spatial interpolation method. The best combination was achieved using Kriging interpolation and weed sampling on the finest grid. Additionally, using Gaussian copula interpolation did not reduce the smoothing of minimum and maximum weed densities, which still poses a challenge when employing spatial interpolation methods for SSWM.

The generated weed distribution maps were used to integrate weed functional traits into the weed control decision for SSWM. Species-specific functional traits representing service (e.g., links to phytophagous insects, pollinators, and birds) and disservice potential (e.g., specific leaf area, links to pest species, and vegetative plant height) were extracted from published datasets. Each (dis-)service trait was weighted for every pixel of the weed distribution map based on the density of the weed species present. Consequently, two maps were created: one illustrating the service potential distributed across the field and the other depicting the disservice potential due to the weed composition. The ratio between the (dis-)service distribution maps builds the basis for the weed control maps. Afterwards, weed control was recommended for field areas where the weed composition showed high competitive ability and low biodiversity functions.

The weed control recommendations of this novel approach were compared with those of two currently used economic threshold concepts. The economic thresholds facilitate control recommendations based on the lowest possible economic risk, but neglect the impact of controlling ecologically relevant weed species. By incorporating weed functional traits into this novel approach, the area recommended for treatment was, on average, smaller than the area recommended for treatment based on economic thresholds for the study fields. Even areas with higher service than disservice potential were recommended for treatment according to these economic thresholds. The presented approach, based on functional weed traits, could be further enhanced by considering the economic profitability of weed treatment, additional traits that describe the weeds' (dis-)service potential, and replacing manual weed sampling with field-wide automatic observation.

Overall, this thesis's results confirm that the service potential of weeds can be considered separately from their disservice ability in decision-making for SSWM. The present approach is a valuable tool for promoting greater weed species diversity in arable systems while reducing herbicide input.

Zusammenfassung

Im landwirtschaftlichen Kontext werden Unkräuter oft als schädlich angesehen, da sie mit Kulturpflanzen um Licht, Wasser und Nährstoffe konkurrieren. Allerdings erbringen Unkräuter auch bedeutende Ökosystemleistungen, etwa durch die Förderung von Bestäubern, natürlichen Feinden von Schädlingen sowie bestimmten Vogelarten. In dieser Arbeit wird ein Ansatz vorgestellt, mit dem funktionelle Unkrauteigenschaften mit räumlichen Unkrautverteilungskarten verschnitten werden. Die Unkrauteigenschaften beschreiben den negativen Einfluss auf die Produktivität von Kulturpflanzen (*Disservice*-Potential) sowie das Potential zur Erbringung von nützlichen Ökosystemleistungen (*Service*-Potential). Basierend auf den resultierenden räumlichen Informationen können Behandlungsentscheidungen für ein standortspezifisches Unkrautmanagement (engl. *site-specific weed management*, SSWM) getroffen werden. Bei einem SSWM-Ansatz wird die Unkrautbekämpfung gezielt auf jene Bereiche des Feldes beschränkt, in denen eine bestimmte Unkrautdichte vorliegt, wodurch pflanzenspezifische Entscheidungen getroffen und der Herbizideinsatz reduziert werden kann.

Die erste Herausforderung eines SSWM besteht darin, die räumliche Verteilung der Unkrautarten repräsentativ abzubilden, ohne eine flächendeckende Erhebung durchzuführen. Eine mögliche Vorgehensweise für eine ganzflächige Erfassung ist die Bestimmung der Unkrautdichten mithilfe eines georeferenzierten Rasters und anschließender räumlicher Interpolation. Um die optimale Kombination aus der Anordnung des Probenahmerasters und der räumlichen Interpolationsmethode zu ermitteln, wurden unterschiedliche Kombinationen ausgewertet. Die besten Ergebnisse wurden mit der *Kriging*-Interpolation und einer Erhebung am Raster mit der feinsten Auflösung erzielt. Der Einsatz von *Gaussian copula* Interpolation verringerte die Glättung der minimalen und maximalen Unkrautdichten nicht, was bei der Anwendung von räumlichen Interpolationsmethoden für SSWM eine Herausforderung darstellt.

Die erstellten Unkrautverteilungskarten dienten dazu, die funktionellen Eigenschaften der im Versuchsfeld vorkommenden Unkrautarten in das SSWM zu integrieren und kartographisch abzubilden. Artspezifische funktionelle Merkmale, die das *Service*-Potential (z. B. Verbindungen zu phytophagen Insekten, Bestäubern und Vögeln) und das *Disservice*-Potential (z. B. spezifische Blattfläche, Verbindungen zu Schädlingsarten und vegetative Pflanzenhöhe) beschreiben, wurden veröffentlichten Datensätzen entnommen und für jeden Pixel der Unkrautverteilungskarten gewichtet. Aus dieser Berechnung resultierten zwei Karten: eine stellt

das über das Feld verteilte S*ervice*-Potential und die andere das *Disservice*-Potential in Abhängigkeit von der Unkrautzusammensetzung dar. Das Verhältnis zwischen diesen Karten bot die Grundlage der Behandlungsempfehlung für das SSWM: Eine Unkrautbehandlung wird ausschließlich in den Bereichen des Feldes empfohlen, die aufgrund der Unkrautzusammensetzung ein hohes *Disservice*-Potential und geringes *Service*-P*otential* aufweisen.

Die resultierenden Empfehlungen zur Unkrautbehandlung wurden mit denen von zwei derzeit verwendeten ökonomischen Schadschwellenkonzepten verglichen. Die Behandlungsentscheidungen basieren auf dem geringstmöglichen wirtschaftlichen Risiko, vernachlässigen allerdings das Potential zur Erbringung von Ökosystemleistungen. Die zu behandelnde Fläche in den Versuchsfeldern war kleiner, wenn die funktionalen Unkrauteigenschaften in die Managemententscheidung einbezogen wurden, im Vergleich zu den ökonomischen Schadschwellenkonzepten. Auf Grundlage der ökonomischen Schadschwellenkonzepte wurde für die Bereiche im Feld mit höherem *Service*- als *Disservice*-Potential eine Unkrautbehandlung empfohlen.

Der vorgestellte Ansatz, der auf funktionellen Unkrauteigenschaften basiert, könnte weiter verbessert werden, indem die ökonomische Rentabilität der Unkrautbehandlung berücksichtigt wird, zusätzliche Unkrauteigenschaften einbezogen werden und die manuelle Unkrauterfassung durch eine flächendeckende automatische Beobachtung ersetzt wird.

Insgesamt bestätigen die Ergebnisse dieser Arbeit, dass das *Service*-Potential von Unkräutern getrennt von ihrem *Disservice*-Potential betrachtet und in die Behandlungsentscheidung für ein SSWM integriert werden kann. Der vorgestellte Ansatz ist ein nützliches Instrument zur Förderung einer größeren Artenvielfalt in Ackerbausystemen bei gleichzeitiger Reduzierung des Herbizideinsatzes.

Table of Contents

1. General Introduction

Weeds are integral to agricultural systems and compete with arable crops for essential resources, such as light, water, and nutrients. Without proper management, weeds can reduce the average global yield by up to 34%, according to a coarse global-level (Oerke, 2006). This indicates a greater risk of crop yield loss than that posed by animal pests and pathogens. In this thesis, weed management is defined as a holistic approach encompassing a range of strategies to regulate weed populations over the long term (e.g., crop rotation, crop varieties, or tillage). Whenever direct and immediate reactions are addressed to reduce the negative impact of weeds on crop production, the term weed control is used (e.g., mechanical removal, chemical treatment, or biological control). Chemical weed control using herbicides is widely applied in conventional agriculture, providing an effective and economical method to increase crop yields' quality and quantity with a reasonable investment of labor and time (Sharma et al., 2019).

In recent decades, it has become evident that herbicide use can produce adverse agronomic and ecological effects. While few new herbicidal modes of action have been introduced since the 1970s, herbicide resistance has evolved in several important weed species, diminishing the long-term effectiveness (Westwood et al., 2018). Additionally, herbicides and their metabolites may enter surface waters through runoff, leach into groundwater, and volatilize into the air, potentially harming non-target organisms (Kortekamp, 2011), such as pollinators (Riggi et al., 2022), earthworms (Pelosi et al., 2013), arthropods (Mehdizadeh et al., 2021), as well as human health (Mohd Ghazi et al., 2023). To mitigate the negative impacts of herbicide use, political measures, such as the Farm-to-Fork strategy of the European Union, aim to regulate the sustainable use of herbicides and seek a reduction of pesticide use by about 50% by 2030 (European Commission, 2020).

Besides the competitive effects, weeds also provide positive impacts on agroecosystems by delivering essential ecosystem services, such as supporting pollinators, birds, natural enemies of pest species (Marshall et al., 2003), and reducing soil erosion (Ruiz-Colmenero et al., 2013). Beyond the direct adverse effects of herbicide residues on the environment, the decline in weed species diversity in agricultural fields caused by chemical weed control can lead to decreased available food sources and host options for higher trophic levels of the agroecosystem (Koch and Hurle, 1978; Kubiak et al., 2004). As a conclusion to the high intensification of farming practices — like the simplification of crop rotations, increased nitrogen fertilization rates, and weed control with highly effective herbicides — weed species diversity in agricultural landscapes has decreased, resulting in a loss of beneficial service functions in arable fields (Hyvönen and Salonen, 2002; Potts et al., 2010; Storkey and Westbury, 2007). Therefore, enhancing biodiversity in agricultural systems requires urgent measures to conserve and promote weed diversity (von Redwitz et al., 2025). In addition to ecosystem services provided by weeds, studies indicate that high weed diversity can provide economic benefits compared to a less heterogeneous weed composition (Storkey and Neve, 2018). Fields with low species diversity in weed composition are often dominated by highly competitive weed species that are difficult to control (Storkey and Neve, 2018). Overall, reducing herbicide application is crucial to preserving and enhancing arable weed diversity.

1.1. Site-Specific Weed Management

One approach to reduce herbicide input is the implementation of site-specific weed management (SSWM), which considers the within-field spatial distribution of the weed population. This method allows for precise weed control by targeting treatment to spatial areas of the field with specific weed densities (Dehsorkhi et al., 2025; Gerhards et al., 2022). The concept is based on the observation that weeds are often not evenly distributed across a field and tend to grow in aggregated patches (Blank et al., 2023; Heijting et al., 2007). Therefore, conventional field-wide herbicide application, irrespective of the spatial weed distribution, often leads to unnecessary herbicide spraying in weed-free areas of the field.

SSWM is implemented in the following sequence: (a) weed sampling in the arable field; (b) creating weed distribution maps by analyzing spatial patterns; and (c) defining optimal weed control actions (Figure 1.1). In the final step (d), weed control treatments are applied e.g., by using advanced sprayer technologies that precisely manage herbicide application through boom section control, individual nozzle control, and patch or spot spraying techniques. These systems target only specific areas of the fields with particular weed densities (Fernández-Quintanilla et al., 2018). The potential for herbicide savings due to SSWM relies on the level and spatial pattern of weed infestation within the field and herbicide reduction is estimated to range between 6–81% depending on the crop species (Gerhards and Oebel, 2006; Spaeth et al., 2024). In addition to SSWM with chemical weed control, mechanical, physical, or thermal methods can target individual weed plants or patches using technologies such as lasers, weeding robots, or steam, although these approaches are currently less commonly practiced (Reuter et al., 2025).

The weed detection in arable fields can be categorized into two main approaches: offline and online weed detection. The already mentioned sequence of steps in the SSWM (depicted in Figure 1.1) represents the offline approach, as all steps from weed detection (a, b) to subsequent weed control treatment (d) are carried out as distinct steps. In contrast, online detection integrates these processes into a single operation, by identifying and controlling weeds simultaneously in the field — e.g., using a sprayer system with automatic weed detection compatible with SSWM. While the offline strategy allows for more targeted planning in advance of weed control, including determining the required herbicide amount and application effort (e.g., pre-determining driving paths, necessary crossings), it is generally more time-consuming. This thesis focuses on offline SSWM, which enables a calculation of more detailed weed control recommendations based on pre-created weed distribution maps, considering the weed species composition.

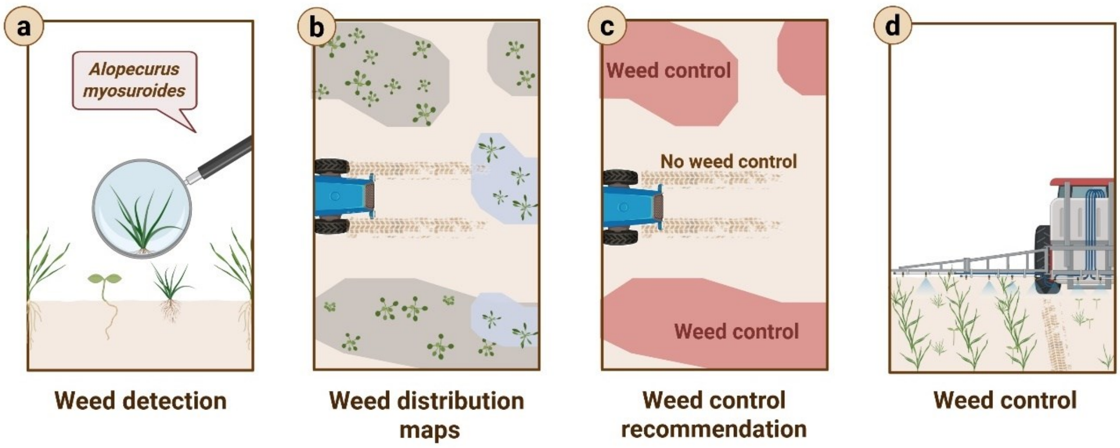

Figure 1.1: Process in SSWM: (a) weed detection and identification of weeds, (b) the creation of species-specific weed distribution maps, (c) the creation of weed control maps, and (d) the weed control treatment targeted to the areas to be treated from the weed control map.

1.1.1. Weed Distribution Maps

A successful implementation of SSWM relies on accurate knowledge of the spatial weed distribution within the field (Gerhards et al., 2022). The spatial distribution is influenced by management practices, the biology of weed species, and site- and field-specific characteristics, such as soil type and texture (Mortensen et al., 1998). While some weed species form large, discrete aggregated patches, others aggregate into many small, diffuse patches (Blank et al., 2023; Heijting et al., 2007). Assessing weed distributions manually over the entire arable field is too cost- and time-intense. Therefore, manual surveys of weed densities at predefined grid points are primarily used to describe the weed infestation in the field. Following grid sampling, spatial interpolation is applied to estimate the weed distribution in areas between the sampling grid points by deriving approximate values from the observed weed densities recorded at the sampling locations. Spatial interpolation offers a cost-effective, time-saving method for creating field-wide weed distribution maps.

Inverse Distance Weighting (IDW) and Kriging are two commonly used interpolation methods for mapping weed distribution based on manual grid sampling. The IDW method is based on the assumption that the variable is more strongly correlated with its closer neighbours and predicts weed densities based on the distance between the estimated and the sampled grid points (Kolářová and Hamouz, 2016). The Kriging interpolation method is a geostatistical method considering the optimal linear unbiased predictor for estimating the spatial distribution of weeds (Cousens et al., 2002). Concerns have been raised regarding Kriging interpolation, as the assumption of a linear distribution of weed densities can result in smoothed values when applied to discrete sampling data (Dille et al., 2003; Rew et al., 2001). The smoothing effect describes the tendency of interpolation predictions to underestimate local extreme values (maximum and minimum weed densities), thereby reducing the accuracy of the resulting map (Dille et al., 2003; Rew et al., 2001). Further research aimed at optimizing the accuracy of field-wide weed distribution maps, such as through improved grid sampling and interpolation, could enhance the adoption of SSWM. An approach that could better describe a patchy weed occurrence is the Gaussian copula interpolation, which can describe the dependence structure of multivariate distributions separately from their univariate marginal (Atalay and Tercan, 2017). By now, Gaussian copula interpolation has not been tested to predict weed distribution.

Although a higher spatial resolution of grid points in the field significantly increases the accuracy of weed distribution and density assessment, the associated time and cost requirements for a manual assessment of weeds at numerous grid points are generally too high for practical, large-scale use. To ensure that SSWM is economically viable, the cost of weed sampling must be lower than the savings achieved through reduced herbicide use, including herbicide and application costs (Timmermann et al., 2003). Therefore, developing automated methods for assessing weed density and distribution in the field significantly enhances the practicality and attractiveness of SSWM. Sensor technologies, such as RGB, multispectral, and hyperspectral cameras, mounted on Unmanned Aerial Vehicles (UAVs) or All-Terrain Vehicles (ATVs), could enable automated image acquisition directly in the field. For this, a high image resolution is necessary to identify weed species-specific characteristics using image recognition algorithms, such as frequently employing convolutional neural networks (CNN).

1.1.2. Weed Control Maps

Once the spatial weed distribution in the field is assessed, decision support concepts help to decide whether weed control is required for each defined spatial area. Different concepts for weed control recommendation exist, varying in their complexity, input data requirements, and spatial resolution of the output decisions. The most common concept is based on simple economic threshold values, developed in the 1980s. The threshold value describes the weed density at which the cost of the damage due to the weed infestation exceeds the price of the herbicide treatment (Gerowitt and Heitefuss, 1990). A weed control treatment is recommended if the weed infestation of a single taxonomic group (mono- or dicotyledonous weeds) reaches a threshold value. This decision is generally taken at the field-wide level with a single weed control decision (blanket herbicide application recommended or no application recommended). An integration of economic thresholds into SSWM was tested by Keller et al. (2014), with higher herbicide saving potential than a decision at the field-wide level (Figure 1.2 (b)). A survey by Hamouz et al. (2013) showed potential herbicide savings using economic thresholds in SSWM of 15–100% without reducing winter wheat yield. Therefore, the herbicide application in SSWM could be further reduced by including economic thresholds for taxonomic weed groups in the decision-making step (Keller et al., 2014). Fixed economic thresholds have evolved into field-specific models, developed in Germany in the late 1990s, that support cost-based, species-specific weed control recommendations through decision-support systems like CeBruS (Werner et al., 2004). Based on cost models, these economic threshold decision concepts enable economically feasible weed control recommendations for individual weed species composition (Bensch et al., 2025).

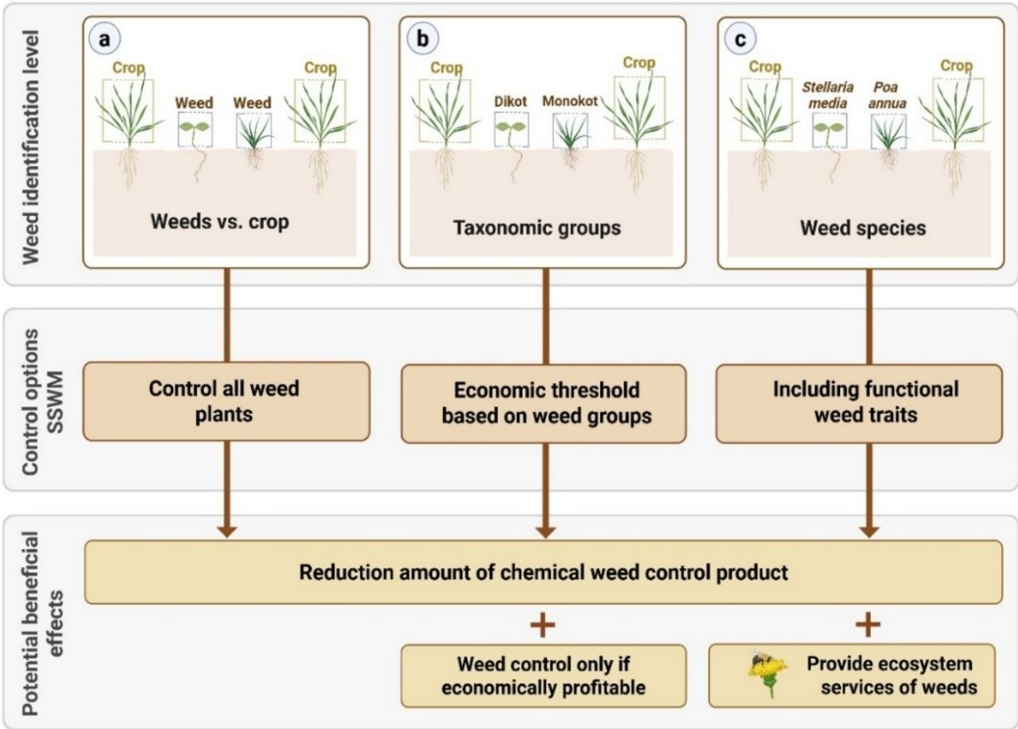

Figure 1.2: Level of weed identification and decision-making options for SSWM addressed in this thesis.

Economic considerations have traditionally formed the basis for decision-making in SSWM approaches. However, the importance of including the ecosystem services of weeds in the decision-making process has been mentioned for many decades (Franz, 1978; Steiner, 1968), with increasing scientific attention in recent years (Esposito et al., 2023; Gerhards et al., 2022; Steinmann et al., 2021; Westbrook et al., 2024). The focus on integrating weed functional traits into weed control recommendations increased with the rapid development of sensor systems for automated weed recognition, which may enable a fully automatic identification and location of weeds at the species level in the near future (Torres-Sánchez et al., 2021; Wang et al., 2024). Therefore, exploring how species-level weed identification can be effectively incorporated into weed control concepts like SSWM is crucial. Functional traits describe biological characteristics of weed plants that influence weed plant performance, survival, reproduction, or interactions with the environment and other species. They describe the weed plant's ability to uptake resources and compete with the crop. Also, functional traits could describe the ability of weeds to provide beneficial ecosystem services (Yvoz et al., 2022). Weeds have a crucial role in agricultural ecosystems by providing seeds that feed farmland birds, support natural enemies of pest species, and phytophages insects (Marshall et al., 2003). Moreover, weeds reduce soil erosion by covering the soil (Seitz et al., 2019) and offer nectar and pollen for pollinators like bees (Requier et al., 2015). Overall, novel weed control decision concepts should focus on reducing herbicide use by primarily targeting highly competitive weed species while promoting those that enhance agrobiodiversity across multiple trophic levels. Esposito et al. (2023) refer to this concept as neutral weed communities, describing weed communities that coexist with crops without significantly reducing crop yield or quality compared to weed-free conditions. These weeds can be conserved for the provision of ecosystem services and the maintenance of biodiversity in arable fields (Figure 1.2 (c)).

1.2. Study Design and Research Objectives

This section outlines the overall study design and objectives that guided the research of this thesis. *Chapters 2* to *4* comprise three consecutive studies, each focusing on advancing SSWM approaches by investigating an improved weed sampling strategy or by studying an innovative concept for weed control recommendations based on weed functional traits.

Chapter 2 starts with the fundamentals of efficient weed control recommendations for SSWM: mapping weed infestation and distribution in arable fields. The optimal combination of sampling grid design and commonly used interpolation methods for predicting weed densities between grid sampling points are studied. Various factors, such as the number of sampling points, their spacing, and spatial arrangement, are assessed for their impact on the accuracy and reliability of interpolation results. To do this, weed sampling was conducted in four arable fields near Brunswick (Central Germany) with varying weed distributions and densities, utilizing a counting frame and predefined grids with different resolutions and arrangements of grid points: random versus regular arrangements of 40 grid points, as well as a combination of both grid types (fine grid). Based on the sampled weed densities, six interpolation techniques have been compared to create weed distribution maps: Ordinary Kriging, Simple Kriging, Universal Kriging, Gaussian copula Kriging, Nearest Neighbor, and Inverse Distance Weighting. The patchiness index was analyzed for all twenty weed species observed in the study fields and tested for its impact on prediction quality. *Chapter 2* addresses the following research questions:

- Which interpolation method predicts the weed distribution most accurately?
- Are weed samplings with randomly distributed sampling grid points more accurate for interpolation in comparison to a regularly distributed sampling grid?
- Does the Gaussian copula interpolation method overcome the smoothing of maximum and minimum weed densities?

The findings of this study enhance weed mapping strategies and support more precise weed control treatments in the future.

The *Chapter 3* and *Chapter 4* focus on the decision-making process for SSWM as an integrated step between weed detection and weed control. The study in *Chapter 3* presents a novel approach that incorporates weed functional traits into the weed control map for SSWM, which was tested for a study field near Brunswick (Central Germany). The novel approach defines field areas with high potential for beneficial ecosystem services provided by weeds (service potential) and field areas with negative impacts on crop productivity (disservice potential). To apply the approach, weed functional traits describing the service potential (e.g., flowering duration, link to pollinators, or birds) and disservice potential (e.g., plant height, specific leaf area, link to pest species) for each weed species observed in the study field were collected from published literature. Using Kriging Interpolation, weed distribution maps were created for all weed species observed. A pixel-wise calculation was used to weight the trait values (normalized to values between 0 to 1) based on the weed density in the species-specific distribution maps. A principal component analysis condensed the resulting trait distribution maps into two spatial field maps: the disservice and service distribution maps. The relation between service and disservice potential has been formed the basis for the weed control recommendations in the final step. The approach can be a helpful step between weed monitoring and weed control treatment that allows weed control strategies to be site-specific and tailored to the individual weed species and their functional traits. The following research question guided the development of the approach:

- How can weed functional traits describing service and disservice potential be considered in the weed control map for SSWM?
- Can the service potential be considered separate from the disservice potential of weeds?

The approach presented in *Chapter 3* is compared with two concepts currently used for weed control decision-making in *Chapter 4*. The other two concepts are based on the economic profitability of the weed control treatment (economic threshold concepts); one addresses weed taxonomic groups, while the other provides species-specific recommendations. For the economic threshold concepts, a weed control treatment is recommended if the weed density (plants m^{-2}) reaches the threshold value for the taxonomic group or the species-specific threshold value. The study examines the differences in herbicide treatment recommendations for SSWM among these decision-making concepts. For this purpose, weed sampling was conducted at five sites with winter wheat and winter barley in Germany, including one site near Cologne (Western Germany) and four sites near Brunswick (Central Germany). Using Inverse Distance Weighted interpolation, weed distribution maps were created for all weed species and study sites. Afterwards, the weed distribution maps were used to generate site-specific weed control recommendations based on the economic threshold concepts and the trait-based concept presented in *Chapter 3*. The final weed control maps of the different concepts were compared using a similarity index and by analysing the spatial distribution of the recommendations. The present study answers the following research questions:

- Do weed control recommendations based on the economic threshold concepts differ for SSWM compared to the current single field-wide decision?
- What are the potential benefits and disadvantages of each threshold concept?
- Do weed control recommendations for SSWM change when weed functional traits are incorporated into the decision-making process?

A general discussion follows in *Chapter 5*, where the findings from all three studies are synthesized and interpreted in the context of the research objectives and their practical implementation. The following chapters present each study in detail, including their methods, results, and discussion.

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2. Estimation of Weed Distribution for Site-Specific Weed Management—Can Gaussian Copula Reduce the Smoothing Effect?

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2.1. Abstract

Creating spatial weed distribution maps as the basis for site-specific weed management (SSWM) requires determining the occurrence and densities of weeds at georeferenced grid points. To achieve a field-wide distribution map, the weed distribution between the sampling points needs to be predicted. The aim of this study was to determine the best combination of grid sampling design and spatial interpolation technique to improve prediction accuracy. Gaussian copula as alternative method was tested to overcome challenges associated with interpolating weed densities such as smoothing effects.

The quality of weed distribution maps created using combinations of different sampling grids and interpolation methods was assessed: Inverse Distance Weighting, different geostatistical approaches, and Nearest Neighbor Interpolation. For this comparison, the weed distribution and densities in four fields were assessed using three sampling grids with different resolutions and arrangements: Random vs. regular arrangement of 40 grid points, and a combination of both grid types (fine grid).

The best prediction of weed distribution was achieved with the Kriging interpolation models based on weed data sampled on the fine grid. In contrast, the lowest performance was observed using the regular grid and the Nearest Neighbor Interpolation. A patchy distribution of weeds did not affect the prediction quality.

Using the Gaussian copula kriging did not result in a reduction of the smoothing effect, which still represents a challenge when employing spatial interpolation methods for SSWM. However, using a randomly distributed raster with a fine resolution could further optimize the precision of weed distribution maps.

Keywords: Site-specific weed management, interpolation, weed distribution maps, raster, sampling grid arrangement

2.2. Introduction

Site-specific weed management (SSWM) is an approach developed to deliver more efficient and sustainable crop production through more precise weed management, considering the spatial distribution of weed populations on agricultural land (Brain and Cousens, 1990; Gerhards et al., 2022). As part of SSWM, weed control (i.e., mechanical or chemical) is performed by considering the individual distribution of weed plants or weed nests across individual fields. Several SSWM approaches exist: In the real-time approach, weeds are automatically detected and a treatment decision and application are instantly made in the field (e.g., a tractor equipped with an automatic weed detection and a spraying system suitable for SSWM). In contrast, the steps 'weed detection' and 'weed management' are separated in the pre-planned 'mapping' approach. Afterwards, the management can be target to the areas in the field where weeds were observed.

Even though previous research has indicated a high potential for herbicide savings through SSWM (Gerhards and Oebel, 2006; Timmermann et al., 2003), and the required technology has shown strong advancements in recent years, SSWM is not frequently implemented by farmers (Gerhards et al., 2022). One reason is the high cost and time requirements to accurately sample the in-field distribution of weeds. This is especially difficult, as weeds are often distributed in patches on arable fields (Blank et al., 2023; Nordmeyer, 2006). Novel weed sampling approaches utilizing technologies like 3D cameras, remote sensing, multi-spectral imaging, and Artificial Intelligence (AI) for automatic weed species classification and can massively increase the speed and accuracy of weed mapping. The use of Unmanned Arial Vehicles (UAV) or All-Terrain Vehicle (ATV) and image recognition pipelines already allows for an automatic differentiation between the crop and weeds while classification of weeds at the species-level is a challenge still to be solved (von Redwitz et al., 2022). A further improvement in weed detection on the species-level enables the inclusion of functional traits of each weed species into the SSWM (Schatke et al., 2024). Areas in the field with a high competitive ability due to the weed composition can be identified and managed separately from the areas in the field with high ecological services due to the weeds. High resolution and species-specific weed distribution maps are a prerequisite for such approaches. Further research on optimal weed sampling and detection methods employing technologies, such as remote sensing and AI, is therefore crucial for supporting the adaption of SSWM (Gerhards et al., 2022). For wheat, distinguishing crop plants from weeds, especially grass weeds, is difficult due to the minimal differences in color and spectral characteristics in their early growth stage (Liu, T. et al., 2024; Liu, Y. et al., 2024; Wang et al., 2024). While most studies focused on crops with wide-spaced rows like maize and sugar beets, the weed detection using UAV pictures is even more complex in crops like wheat with narrow row spacing (Anderegg et al., 2023). By reducing the altitude of the UAV flight, automatic entire-field weed monitoring with a UAV is limited by battery capacities and a large amount of data to be stored, processed, and analyzed (Anderegg et al., 2023; Pflanz et al., 2018).

The weed distribution in a given field can be described by either continuous or discrete data collections (Rew et al., 2001; Rew and Cousens, 2001). While a continuous weed sampling approach considers the entire field and the weed density is assessed qualitatively, for example, on an ordinal (zero/low/medium/high) or categorical (presence/absence) basis, a discrete sampling approach collects data at predefined sampling points distributed within the field. As weeds are only recorded at the grid points and not on the entire field, spatial interpolation approaches are additionally required to map the potential weed distribution between the grid points. As part of this spatial interpolation, approximate values for the weed distribution at specific locations are estimated from the observed values of weed species and densities recorded at the grid points. To do so, interpolation approaches test different functions to represent best the weed distribution over the entire area (Emmendorfer and Dimuro, 2020). Many studies mapping the existing weed distribution based on a spatial grid employed the Kriging interpolation method, a geostatistical method considered as the optimal linear unbiased predictor of values to estimate the spatial distribution of weeds (Cardina et al., 1995, 1996; Cousens et al., 2002; Donald, 1994). On the other hand, concerns regarding this method have been expressed as Kriging assumes a linear distribution of the variable, which can result in smoothed values when it comes to discrete sampling data (Dille et al., 2003; Rew et al., 2001). Due to the smoothing effect of Kriging, the maximum weed densities are predict with lower values and the minimum with higher values when compared to the actual measured weed densities (Dille et al., 2003; Hamouz et al., 2006; Rew et al., 2001). In Kriging, the spatial dependence structure of the underlying random field is modeled by variograms, but this is impaired if the data is not Gaussian distributed (Agarwal et al., 2021). In addition, a variogram only describes the mean dependence between variables and the specific deviation of every point. An approach that could better describe a patchy weed occurrence is the Gaussian copula interpolation, which can be used to describe the dependence structure of multivariate distributions separately from their univariate marginals (Atalay and Tercan, 2017). Regardless its advantages, this approach has not yet been established and tested for the creation of weed distribution maps. A reduction of this smoothing effect can significantly increase the applicability of interpolation for SSWM especially when using fixed weed control thresholds.

Multiple studies suggest that the spacing between the grid points over the field and grid point number is a more critical factor than the choice of the interpolation method (Dille et al., 2003; Rew et al., 2001; Somerville et al., 2021). Often, the conclusion is that the performance of simple interpolation methods is reduced when the number of available sample points is limited. Examining only one type of grid point design can leave a gap in determining the optimal interpolation approach. Therefore, comparing the performance of different interpolation methods for predicting field-wide weed distribution requires testing different spatial grid arrangements and grid point numbers using a consistent study design across different experimental plots and fields.

This study aims to identify the optimal combination of interpolation method and grid design for predicting the weed density (plants per 0.1 m^2) between the sampling grid points in four arable fields with different weed distributions and densities. Six different interpolation methods, including Ordinary Kriging, Simple Kriging, Universal Kriging, Gaussian copula Kriging, Nearest Neighbor, and Inverse Distance Weighting, are compared. The impact of the number of sampling grid points, distance between grid points, as well as spatial arrangement of the grid points on the interpolation results are evaluated. In addition, the sensitivity of the six interpolation methods to variations in species-specific weed occurrence is tested to determine the most accurate and consistent interpolation method for estimating the weed distribution. The smoothing effect of the six interpolation methods on maximum and minimum weed numbers was tested, especially for the Gaussian copula Kriging that has so far not been tested for predicting weed distributions.

2.3. Materials and Methods

2.3.1. Field Trial

A spatial grid for manual weed sampling was installed in a center plot (approx. 24 m x 100 m) of four arable fields in central Germany in 2023 (Figure 2.1). With a mean annual precipitation of 548 mm and a mean annual temperature of 11.5°C in 2023, the study region is classified as according as Cfb according to the 'Köppen climate' classification (Geiger, 1954). Winter wheat (*Triticum aestivum* L.) with a seeding rate of 350 (field 1) and 360 seeds per m^2 (field 2–4) was sown on the 11. and 12. October 2022 on the four fields.

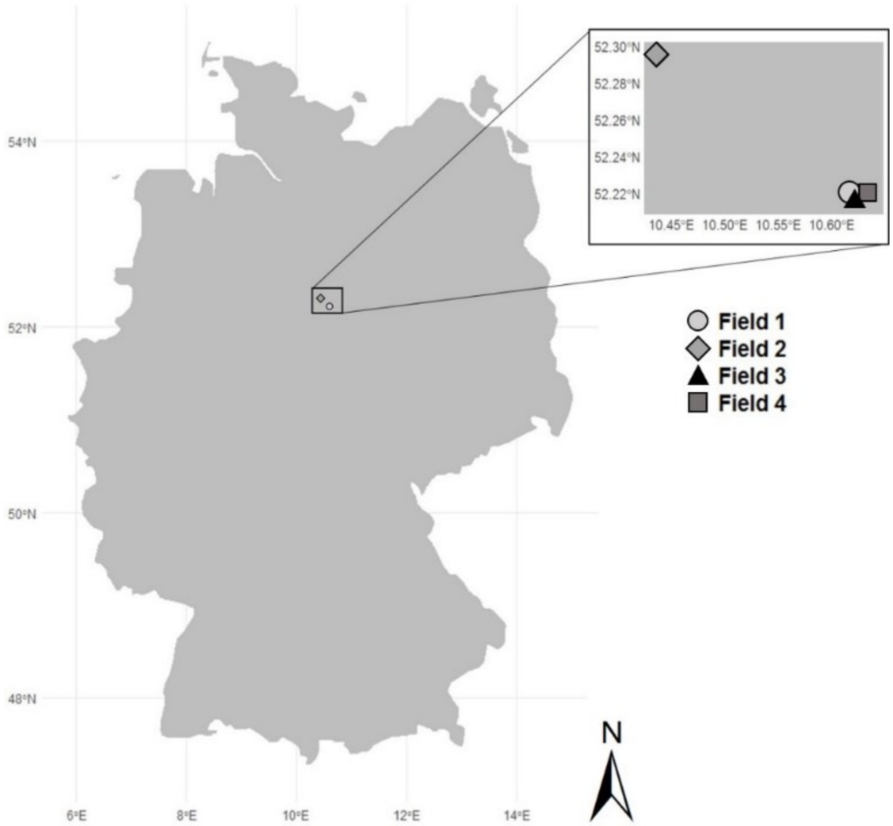

Figure 2.1: Location of the four study fields (fields 1–4) in Germany.

No herbicide treatment was carried out before seeding and within the cropping season of winter wheat in the study area in each field. Fertilizer, growth regulators, fungicide, and insecticide applications were conducted according to common agricultural practices. Two different grid types were installed using a GNSS system in each experimental plot of the four study fields: (1) a regular grid consisting of 40 grid points with a distance of 10 m along the wheat row and 6 m between the rows ('regular grid') and (2) a grid of 40 points randomly distributed over the field plot ('random grid'; Figure 2.2). A third option combined all 80 points of both the regular and the random grid ('fine grid'). None of the grid points was located on and between the tramlines of the tractor. Two times between 21. and 24. March 2023 a manual weed assessment was carried out by the same group of people at each of the 80 grid points at each of the four fields. At each grid point, the present weed species and the weed density (the number of individual plants per species) were determined using a counting frame with an area of 0.1 m^2. The weeds species had a BBCH between 11 and 12 and the winter wheat plants BBCH 12.

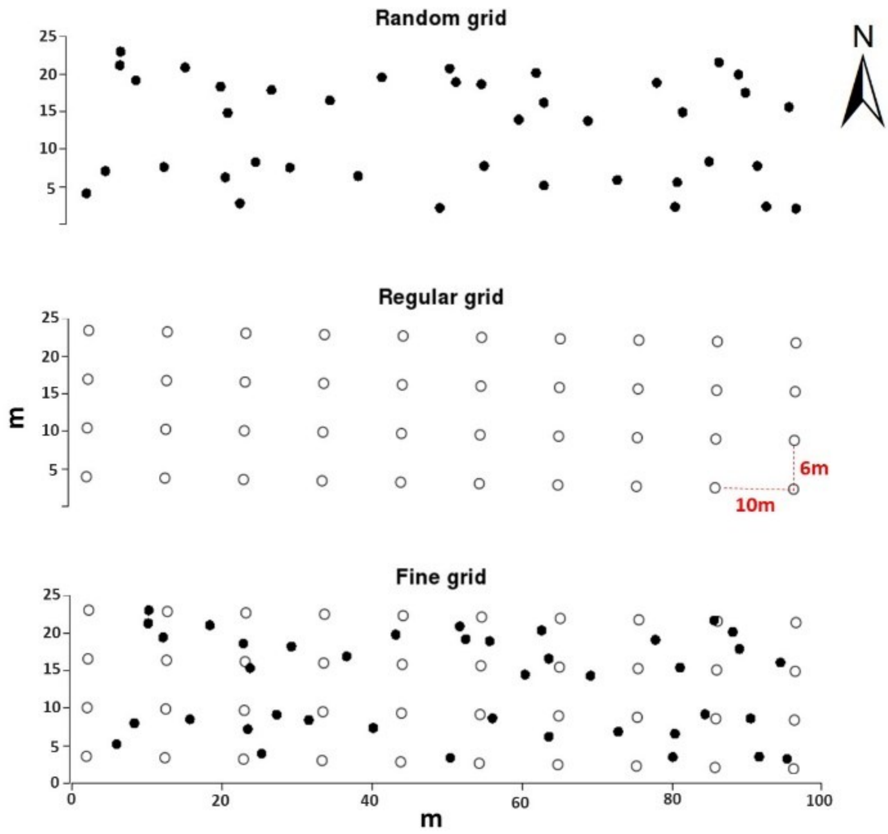

Figure 2.2: Different grid types with 40 (regular and random) and 80 (fine) grid points for weed assessments in a plot of approx. 24 m × 100 m on the four study fields.

2.3.2. Data Analysis

Weed distribution maps for each weed species in the grid area were generated using the packages ‘gstat’ (Pebesma, 2004), ‘raster’ (Hijmans, 2024), ‘gcKrig’ (Han and Oliveira, 2018) in R 4.1.1 (R Core Team, 2023). The weed distribution maps represented the 24 m x 100 m experimental field plot with a pixel resolution of 0.1 m^2 (total 903 x 196 pixels). The number of individual weed plants per species observed at each grid point to test six different interpolation methods was used: Ordinary Kriging (OK), Simple Kriging (SK), Universal Kriging (UK), Gaussian copula (GK), Natural Neighbour (NN), and Inverse Distance Weighting (IDW). The six interpolation methods were tested separately for each observed weed species, the three grid type (regular, random, and fine), and the four fields.

Spatial Distribution of Weeds

To determine how the distribution of weeds affected the prediction quality of the interpolation methods, Lloyd's index of patchiness (PI) was determined in advance based on the data for each species and each grid type (Lloyd, 1967). Given by:

$$PI = \frac{\bar{x} + (\frac{s^2}{\bar{x}} - 1)}{\bar{x}} \tag{2.1}$$

Where $\bar{x}$ is the mean of the observed weed densities and s^2 is the variance in the data. If PI > 1, the weed density is described as an aggregated or patchy distribution across the field. If PI < 1, the weed densities are randomly distributed. An increasing PI index indicates an increase in patchiness.

Inverse Distance Weighting (IDW)

The IDW weights the influence of the observed value based on the distance from the non-observed points for which a prediction is to be made (Musashi et al., 2018). IDW is based on the assumption that the variable is more strongly correlated with its closer neighbors and that the influence of a sampled location on the estimate decreases with increased distance. The weed density to be estimated at an unsampled location is calculated as a weighted average of all sampled values, with the weights determined by the inverse of the distances between the sampled and unsampled locations. The interpolated value at the unsampled location is calculated as:

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i), \tag{2.2}$$

Where $Z(x_0)$ is the predicted value at the unsampled point x_0, λ_i is the weight for the observation point x_i, $Z(x_i)$ is the number of a specific weed species at the observed point x_i and n is the total number of observation points. To describe the weight λ_i, the following equation was used:

$$\lambda_i = \frac{d_i^{-u}}{\sum_{i=1}^{n} d_i^{-u}} \tag{2.3}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{2.4}$$

Where u is the power parameter and d_i the distance between the observation point i and the unsampled location. The power parameter in IDW is a value between 0 and 2, with higher values resulting in less weight given to data points further away from the point being estimated. In this study, the optimal power value based on the smallest NRMSE was selected using a Leave-One-Out Cross-Validation (LOOCV) as described below for model validation. The optimal power value for each species, grid type, and field is listed in supplemental material (Table S1).

Nearest Neighbor (NN)

The NN method is similar to the principle of average weighted interpolation methods such as IDW. It is based on the idea that the variable is strongly correlated with its closer neighbors and that the influence of a sampled location on the estimate decreases with distance. Each unsampled point $Z(x_0)$ is assigned the value of the nearest observed point x_i (Bar-Hen et al., 2015).

Kriging

Kriging is a geostatistical interpolator that estimates the spatial structure of the observed values and is based on generalized least-squares regression algorithms. It assumes that points that are close to each other have a certain degree of spatial correlation, but points that are widely separated are statistically independent. The key step is the modeling of the variance between all pairs of points in the sampled data. The variance variogram Υ expresses the degree of similarity between two observations separated by a given distance d (Equ. 2.5; (Emary et al., 2014)),

$$\hat{\Upsilon}(d) = \frac{1}{2n}\sum_{i=1}^{n}(Z(x_i) - Z(x_i + d))^2 \tag{2.5}$$

With *n* being the number of observation points. In this study all grid points (except the test point) were used for the training. $Z(x_i)$ is the value at point x_i, and $Z(x_i + d)$ is the value at a point separated by distance d from x_i. Afterward a function (Gaussian, spherical or exponential) was fitted to the empirical variogram using the method of weighted least squares, to estimate the variance at all separation distances. Different functions were tested using a Leave-One-Out Cross-Validation (LOOCV) method and chose the one with the lowest NRMSE for each weed species (supplemental material; Table S1). The model functions were then used to determine the weights λ_i such that the estimated variance is less than the variance for any other linear combination of the observed values (Isaaks and Srivastava, 1989). The weights were applied to the sampled points according to the formula:

$$Z(x_0) - \mu = \sum_{i=1}^{n} \lambda_i * (Z(x_i) - \mu) \tag{2.6}$$

Where μ is the average of the data. These resulting weights will depend on the assumptions on the mean value $\mu(x_i)$ as well as on the variogram. This varies slightly according to which type of Kriging is being conducted.

Simple Kriging (SK) assumes that the mean of the observed data μ is *constant* and *known*, so no systematic trend or drift over the area exists. The number of sample points used to make the estimation is determined by the range of influence of the variogram.

$$Z(x_0) = \sum\nolimits_{i=1}^{n} \lambda_i Z(x_i) + \left[1 - \sum\nolimits_{i=1}^{n} \lambda_i\right] \mu \tag{2.7}$$

$\sum_{i=1}^{n} \lambda_i$ is not forced to be 1.

The equation for Ordinary Kriging (OK) is the same as for SK, but the *unknown* and *constant* mean is also estimated from the data and takes into account the variance of the values at the known locations. The expected value function $\mu(x)$ can be determined by regression to take the spatial variation of the expectation into account. The constant mean value is replaced by the location-dependent estimate mean function $\mu(x)$:

$$Z(x_0) = \sum\nolimits_{i=1}^{n} \lambda_i Z(x_i) + \left[1 - \sum\nolimits_{i=1}^{n} \lambda_i\right] \mu(x) \tag{2.8}$$

$\sum_{i=1}^{n} \lambda_i$ is forced to be 1.

Universal Kriging (UK) not only allows for a spatially varying mean but also incorporates a deterministic trend model. The specific form of the mean function will be adapted to the characteristics of the spatial trend in the data. The expected value, $Z(x)$, is a combination of a trend component with a deterministic variation, m_i, and a residual component $\varepsilon(x)$:

$$Z(x_0) = \mu(x) + \varepsilon(x) \text{ and } \mu(x) = E\{Z(x_0)\} = \sum_{i=0}^{n} m_i \gamma_i(x) \tag{2.9}$$

Where $\gamma_i(x)$ are known functions of the coordinates or the known basis function, E the expectation value, and m_i fixed, unknown coefficients/parameters. The residual components $\varepsilon(x)$, is considered a stationary random variable with zero mean.

Gaussian Copula Kriging (GK)

A likelihood-based spatial prediction using Gaussian copula model with discrete marginals was generated (Han & De Oliveira, 2018). The marginal distribution describes the probability distribution of a single random variable, independent of the values of other variables. Only a short introduction to Gaussian copulas is given here; see Bárdossy and Li (2008), Gnann et al. (2018), and Han and Oliveira (2018) for further details. The GK uses a 'Gaussian copula' to model the dependence between the values of interest and the observed values. A copula function couples the marginal distributions of *n* variables with their joint distribution function. The basis of copulas is the Sklar theorem that indicates, that any multivariate joint distribution can be written in terms of univariate marginal distribution functions and a copula. A copula transforms an n-dimensional function with interval [0,1] into a one-dimensional function:

$$C: [0,1]^n \rightarrow [0,1] \tag{2.10}$$

A spatial copula assumes that the marginal distribution F_z stays the same within the study area and within spatial translation, i.e. $C_x(u) = C_{x+d}(u)$. The variables u_n are from a unit interval [0,1], obtained by transforming the observed values via the marginal distribution function $u_n = F_z(Z(x_n))$ and the joint cumulative distribution function F_n.

$$C_x(u) = F_n(F_Z^{-1}(u_1), \dots, F_Z^{-1}(u_n)) \tag{2.11}$$

In Gaussian copula interpolation, the model for $C_x(u)$ is the Gaussian copula C_Γ, with the standard normal distribution function Φ and the n-variate standard normal distribution $\Phi_{\Gamma,n}$, parametrized by a correlation matrix Γ.

$$C(u_1, \dots, u_n) = \Phi_n(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_n); \Gamma) \tag{2.12}$$

The density C of the Gaussian copula is calculated with the identity matrix I by:

$$C_\Gamma(u) = \frac{1}{\sqrt{|\Gamma|}} exp\,(-\frac{1}{2}\begin{pmatrix}\Phi^{-1}(u_1)\\ \vdots \\ \Phi^{-1}(u_n)\end{pmatrix}^T (\Gamma^{-1} - I)\begin{pmatrix}\Phi^{-1}(u_1)\\ \vdots \\ \Phi^{-1}(u_n)\end{pmatrix}) \tag{2.13}$$

With the assumption of stationarity, the correlation between two points, separated by a certain distance, is described by a spatial correlation function. The parameters of the function were optimized with a multivariate maximum likelihood-based approach. For the interpolation, first the observed values x_i were transformed to u_i by using their marginal distribution F_z. Afterwards, the conditional density $\hat{c}(u)$ in probability space is calculated by equation 2.14:

$$\hat{c}(u|u_1, \dots, u_n) = \frac{c_{n+1}(u, u_1, \dots, u_n)}{c_n(u_1, \dots, u_n)} \tag{2.14}$$

The right side of equation 2.14 is obtained by means of equation 2.13, by using Gaussian copula. The estimator $\hat{Z}$ at each interpolation location is then:

$$\hat{Z} = \int_0^1 F_Z^{-1}(u)\hat{c}(u|u_1, \dots, u_n)du \tag{2.15}$$

2.3.3. Model Evaluation

To evaluate the model performance of the interpolation methods, a LOOCV was used. The LOOCV method is particularly suitable for small data sets, as all collected data can be used for the estimation (Robinson and Metternicht, 2006). All observed data except for the data of one random grid point were used for the training of the model. Predicted data for this extracted grid point were used to test the model. Using the model algorithm, this process was repeated for all grid points of the observed data set. Afterwards, the predicted value for each point could be compared with the observed value. Based on the similarity or difference the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Normalized Root Mean Square Error (NRMSE) were calculated:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Z(x_i) - Z(x_0)| \tag{2.16}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z(x_i) - Z(x_0))^2} \tag{2.17}$$

$$NRMSE = \frac{RMSE}{max\big(Z(x_i)\big) - min(Z(x_i))} \tag{2.18}$$

The method that yields the smallest MAE, RMSE and NRMSE is considered the most appropriate interpolation method for estimating the given weed distributions. MAE provides a simple and easily interpretable metric for error evaluation which preserves the unit of the original data. RMSE has also the same unit as MAE but gives higher weight to larger errors due to the squaring operation. This can be useful when large errors are more critical and need to be penalized accordingly. For comparing different models, NRMSE is more useful. The NRMSE relates the error metric to the data's range, allowing for accuracy assessment relative to the data's scale. A NRMSE value of zero means that the predicted values are exact as the observed values and a value of one suggests that the prediction errors are as large as the entire variability in the observed data. The observed maximum weed density at each grid point (per 0.1 m^2) was compared with the corresponding predicted value at that grid point.

To define how accurate the interpolation methods predicts the maximum weed number, the observed maximum value of all grid points was compared with the maximum value predicted by interpolation. The second indicator for a good interpolation prediction is the ability to accurately detect the weed-free areas. In this study, the ‘weed-free area’ described the percentage of the 40 or 80 grid points, where no weeds of the species was observed in the monitoring. For the predicted values, a weed individual plant number less than 0.5 per grid point, was defined as weed-free.

2.4. Results

The four investigated winter wheat fields displayed different numbers of individual plants per weed species and weed distributions. Table 2.1 provides an overview of the mean, minimum and maximum weed plant numbers observed during the weed survey at the 80 individual grid points of the fine grid (sum of regular and random grid points) at the different fields.

Table 2.1: Observed mean number of individual weed plants per 0.1 m^{-2} for each species averaged across the fine grid (80 grid points) on the four study fields. Minimum and maximum weed numbers in the fine grid are provided in brackets (min–max).

Weed species	**Field 1**	**Field 2**	**Field 3**	**Field 4**
Alopecurus myosuroides	2.5 (0–11)	0.1 (0–2)	1.3 (0–4)	0.6 (0–6)
Aphanes arvensis	-	0.3 (0–4)	-	-
Arabidopsis spp.	-	0.1 (0–1)	-	-
Capsella bursa-pastoris	-	0.1 (0–2)	-	-
Cerastrium spp.	-	0.6 (0–6)	-	-
Cirsium arvense	-	-	-	0.2 (0–2)
Lamium amplexicaule	-	2.2 (0–16)	-	-
Lamium purpureum	-	0.2 (0–3)	-	-
Lamium spp.	-	0.1 (0–1)	-	-
Matricaria chamomilla	-	-	11.9 (1–26)	-
Matricaria spp.	0.1 (0–2)	1 (0–11)	-	0.2 (0–2)
Myosotis arvensis	0.1 (0–2)	0.1 (0–2)	-	-
Papaver rhoeas	0.9 (0–9)	0.2 (0–6)	0.03 (0–1)	-
Phacelia tanacetifolia	-	2.5 (0–23)	-	-
Poa annua	-	1 (0–4)	-	-
Polygonum aviculare	0.8 (0–7)	-	0.03 (0–1)	1.1 (0–9)
Sisymbrium officinale	0.1 (0–3)	-	-	-
Stellaria media	-	1.6 (0–14)	-	-
Thlaspi arvense	-	0.6 (0–6)	-	-
Tripleurospermum indorum	-	-	2.4 (0–8)	-
Veronica hederifolia	0.1 (0–2)	-	0.4 (0–3)	-
Veronica persica	-	0.1 (0–2)	-	-
Vicia spp.	0.1 (0–2)	-	-	-
Viola arvensis	5.7 (1–15)	1.5 (0–5)	0.8 (0–6)	0.3 (0–4)

At field 1, nine different weed species were counted in all 0.1 m^2 counting frames across all grid types. A total number of 832 individual plants was observed for field 1 during the weed sampling at the fine grid. The species *Viola arvensis* M. was observed with the highest mean weed number (5.7 plants 0.1 m^{-2}) and highest maximum number (15 plants 0.1 m^{-2}) at the fine grid of field 1. At field 2, 17 weed species were observed across all grid types with total number of individual weed plants of 662, observed using a 0.1 m^2 counting frame at each grid point of the fine grid. The species *Lamium amplexicaule* L. (2.2 plants 0.1 m^{-2}) and *Phacelia tanacetifolia* Benth (2.5 plants 0.1 m^{-2}) showed the highest mean weed plant numbers for the fine grid. Seven weed species were observed at field 3 with a total weed number of 1345 individual plants. Due to the high weed density of *Matricaria chamomilla* L. at field 3 (mean plant numbers of 11.9 plants 0.1 m^{-2}), the total weed number was higher at field 3 than for the other fields. The lowest weed species number (five) and total weed number (181 plants in fine grid) were observed in field 4. The species with the highest mean weed number was *Polygonum aviculare* L. (1.1 plants 0.1 m^{-2}).

For each experimental field, weed distribution maps were generated using the six different interpolation methods and three grid distribution types. The species distribution maps for field 1 are shown in Figure 2.3, while the maps for the three other fields can be found in the Supplements (Figure S1–Figure S3). The maps for field 1 indicate that the species *V. arvensis* showed the highest density (up to 15 individuals per 0.1 m^2). The other weed species occurred at low plant densities and in small patches. The Lloyd’s index of patchiness (*PI)* was the highest for *Myosotis arvensis* (L.) Hill and *Vicia* spp. (both 8.5; regular grid), *Sisymbrium officinale* (L.) Scopoli (13) for random grid and *M. arvensis* (9.4) for the fine grid (Table S1). The species with the highest weed density (*V. arvensis*) also had a *PI* higher than 5 for all grid types. The species with a *PI* value below one were *S. offcinale* and *Veronica hederifolia* L. for the regular grid, *V. hederifolia*, *P. aviculare* and *M. arvensis* for the random, and *V. hederifolia* for the fine grid. The NN method displayed the weed distribution for species with a number higher than 5 plants 0.1 m^{-2} as distinct quadrants with sharp borders when using the data from the regular grid (Figure 2.3). As the grid points are unevenly distributed across the field in the random grid, the resulting values for weed distribution are not divided into quadrants by the NN method, but the borders are also sharp. SK, UK, and OK predicted similar distribution maps for all species. In particular, GK predicted less pronounced patches with higher weed occurrence for all species (except *Papaver rhoeas* L. in regular grid). IDW resulted in a density estimation similar to the predictions of SK and UK, only the patches are slightly more noticeable and less smoothed. While for the species *P. aviculare* and *P. rhoeas* the weed distribution maps based on weed count data sampled by a random grid differ from the ones sampled by the regular grid, they are more similar for the species *Vicia* spp.

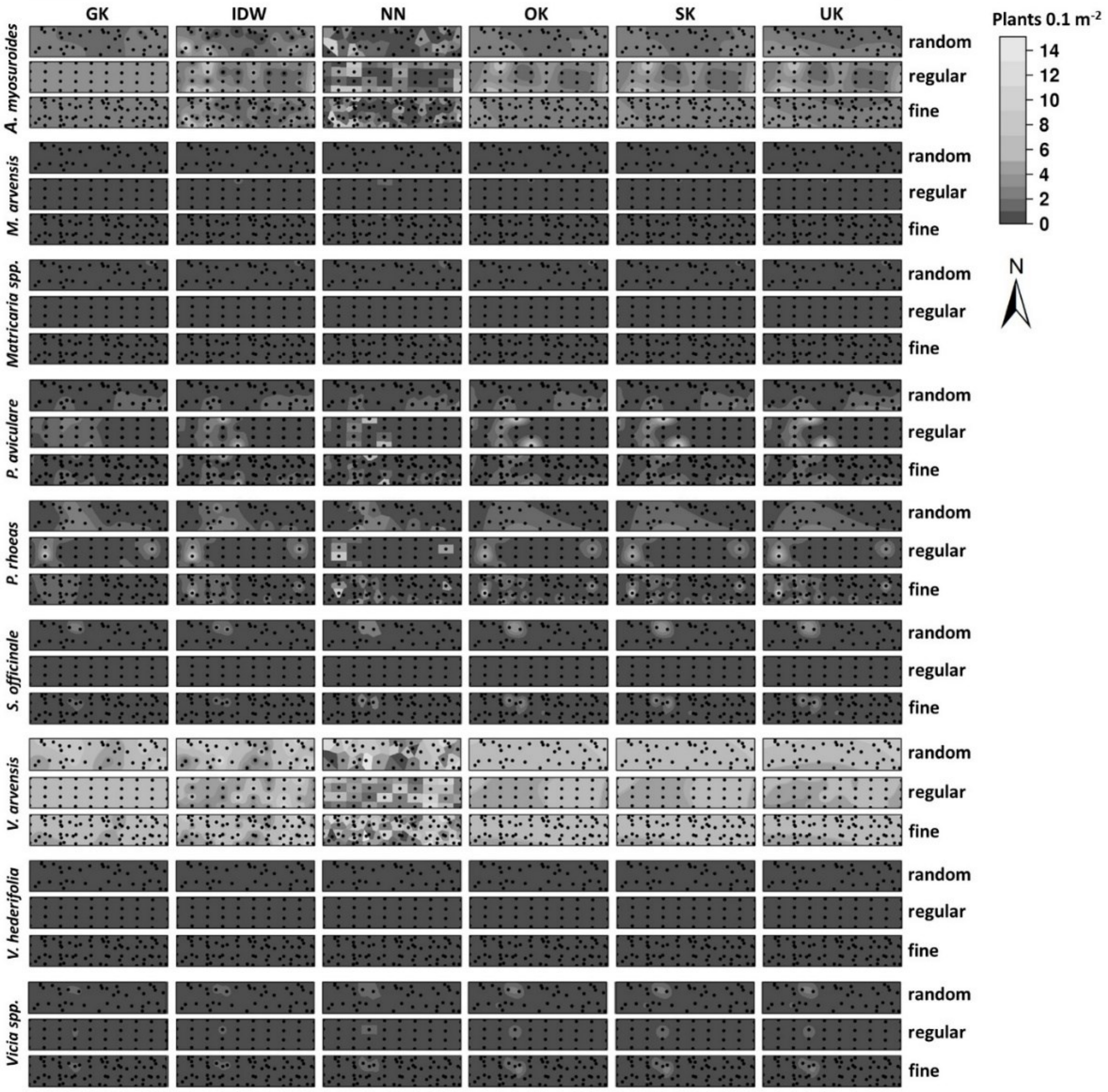

Figure 2.3: Predicted weed distribution (number of plants 0.1 m^{-2}) for the weed species observed at field 1 generated by six interpolation methods – Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK) – based on three different grid types (regular, random, and fine).

2.4.1. Field-, Grid- and Species-Specific Prediction Quality

The prediction quality of the six interpolation methods was determined and recorded separately for each of the four fields and the three grid types. The weed species present in the study fields exhibited different distribution pattern. While some species occurred in patches, others were observed over the entire field plot. It is therefore possible that different settings (grid type, interpolation method) yield distinct fits for different species.

Field 1

The mean NRMSE for all species observed in field 1 was 0.22 for the regular grid, 0.21 for the random, and 0.20 for the fine grid (Figure 2.4). The mean RMSE was highest for the fine grid (1.11 plants 0.1 m^{-2}) consisting of all 80 grid points. To compare the NRMSE between the different species, a mean NRMSE for all interpolation methods was calculated. The species with the highest NRMSE for the fine grid were *V. hederifolia* (0.25), *S. officinale* (0.33) for the regular grid, and *V. arvensis* (0.26) for the random grid. The species with the lowest NRMSE value were *M. arvensis* (0.15; fine), *Vicia spp.* (0.16; regular), *M. arvensis*, and *S. officinale* (0.18) for the random grid. These four weed species were observed with a total density of less than ten plants per 0.1 m^2 in the entire sampling grid. *C*omparing the interpolation methods, the mean NRMSE for all species and grid types was highest for NN (0.26) and lowest for all Kriging methods (0.20). The mean NRMSE for IDW was slightly higher than the Kriging value (0.21). The highest MAE for all interpolation methods and grid types was observed for the species *V. arvensis* (2.61 plants 0.1 m^{-2}).

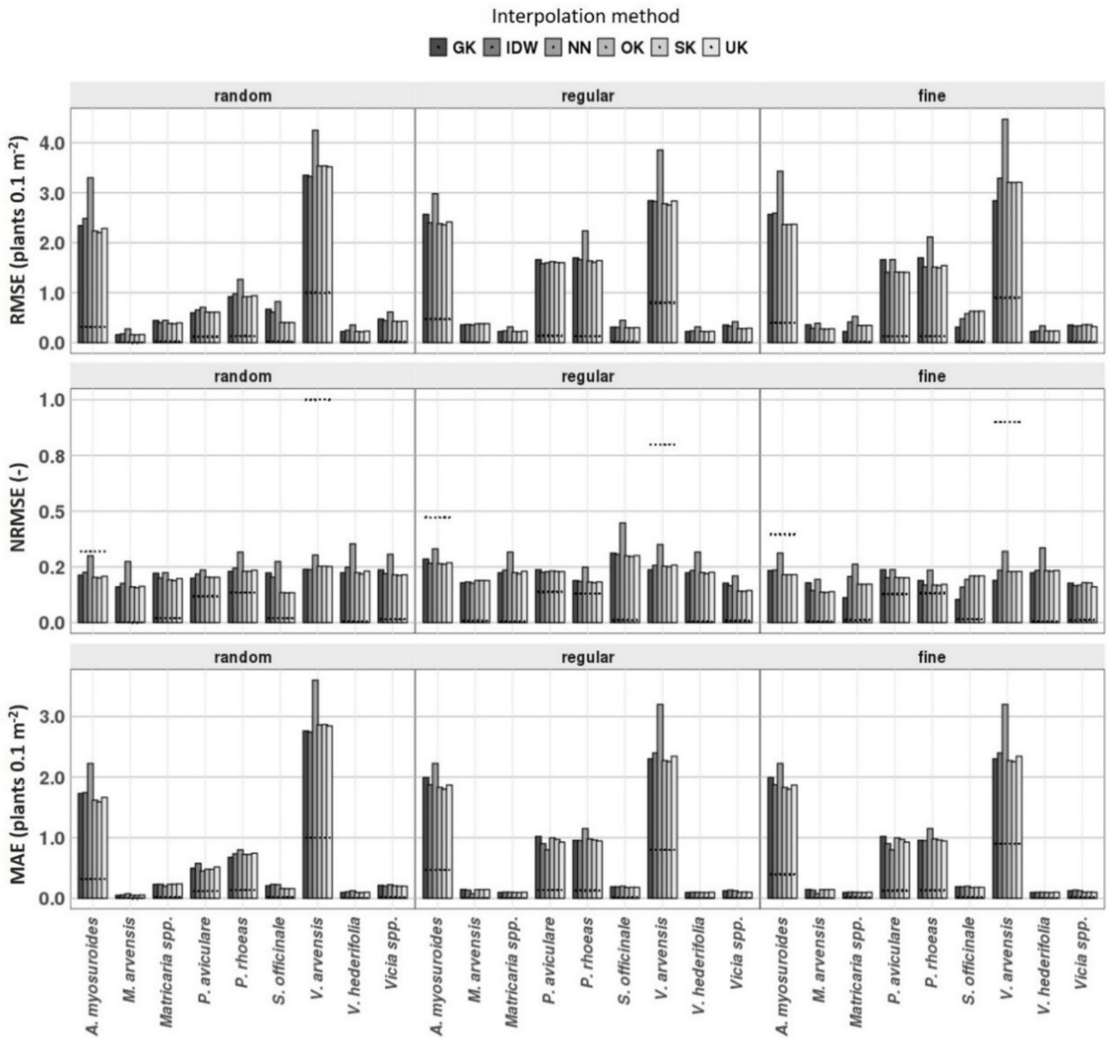

Figure 2.4: Validation results for field 1 and the three grid types (random, regular, and fine). The RMSE, NRMSE, and MAE between observed and predicted values with six different interpolation methods – Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK) – are shown. The dots show the normalized mean weed density observed in the grid sampling.

Field 2

To compare the NRMSE between the species, a mean NRMSE for all interpolation methods was calculated. The mean NRMSE for all species observed in field 2 was similar for all three grid types (Figure 2.5): regular grid (0.24), fine (0.22), and random grid (0.25). The MAE was highest for the fine (0.86 plants 0.1 m^{-2}) and lower for the random (0.67 plants 0.1 m^{-2}) and regular grid (0.73 plants 0.1 m^{-2}). Between the mean MAE (all methods) and mean weed number per species, the correlation coefficient was 0.13. The highest MAE was observed for the species *P. tanacetifolia* with a mean difference between predicted and observed (plants per 0.1 m^2) of

3.37 for fine, 2.19 for regular, and 2.23 for random grid. The mean NRMSE for all interpolation methods was the highest for *Arabidopsis* spp. (0.33) for the random grid, *M. arvensis* for the regular (0.34), and *V. arvensis* for the fine grid (0.34). The weed species with the lowest mean NRMSE were *Cerastrium* spp. (random grid), *Lamium amplexicaule* L. (regular grid), and *Matricaria* spp. (fine grid). The NRMSE was more than twice as high for the weed species with the highest value (*V. arvensis*; 0.34) for the fine grid than for the one with the lowest value (*Matricaria* spp.; 0.15). As the results for field 2 indicated, the NN interpolator resulted in a higher NRMSE (0.30) than the other interpolation methods. The Kriging methods had a mean NRMSE of 0.22 and IDW of 0.24.

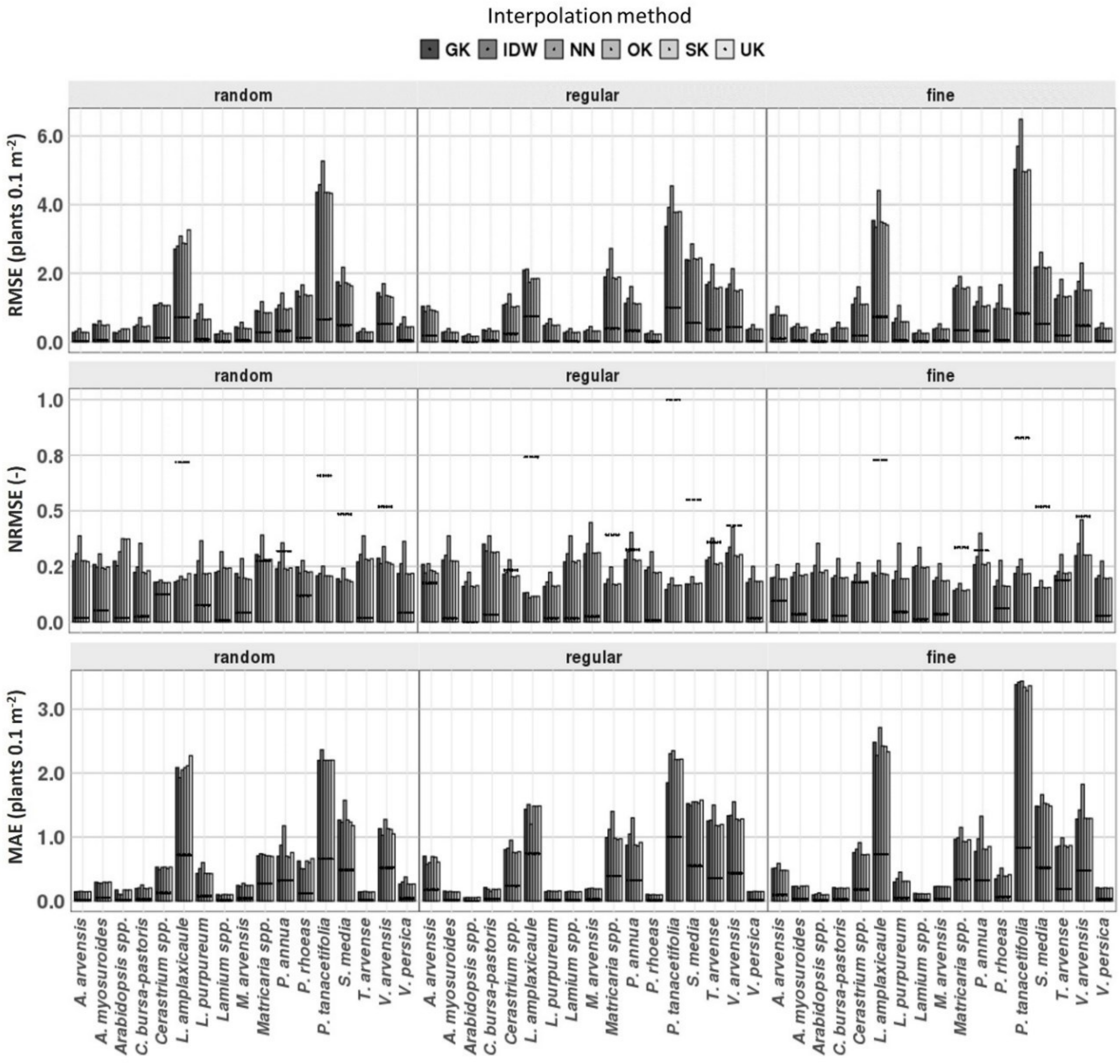

Figure 2.5: Validation results for field 2 and the three grid types (random, regular, and fine). The RMSE, NRMSE, and MAE between observed and predicted values with six different interpolation methods—Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK)—are shown. The dots show the normalized mean weed density observed in the grid sampling.

Field 3

The mean NRMSE for all species observed in field 3 was nearly similar for the regular grid (0.24), the fine (0.21), and the random grid (0.21; Figure 2.6). The MAE was similar for the fine (0.96 plants 0.1 m^{-2}) and random grid (0.97 plants 0.1 m^{-2}) and highest for the regular grid (1.03 plants 0.1 m^{-2}). The correlation coefficient between the mean MAE for all methods and the mean species number was similar to field 1 (0.99). To compare the NRMSE between the species, a mean NRMSE of all interpolation methods was calculated. The NRMSE values for all grids were the highest for the species *Alopecurus myosuroides* Huds. The species with the lowest total weed number (*P. aviculare*) resulted in the lowest NRMSE (0.17) for random grid. For the fine and regular grid, the species with the highest occurrence (*M. chamomilla*) showed the lowest NRMSE (0.14 and 0.17). The difference between the NN interpolation method and the other methods was lower than for the other fields. The NRMSE was 0.28 for the NN methods and 0.21 for the other interpolation methods.

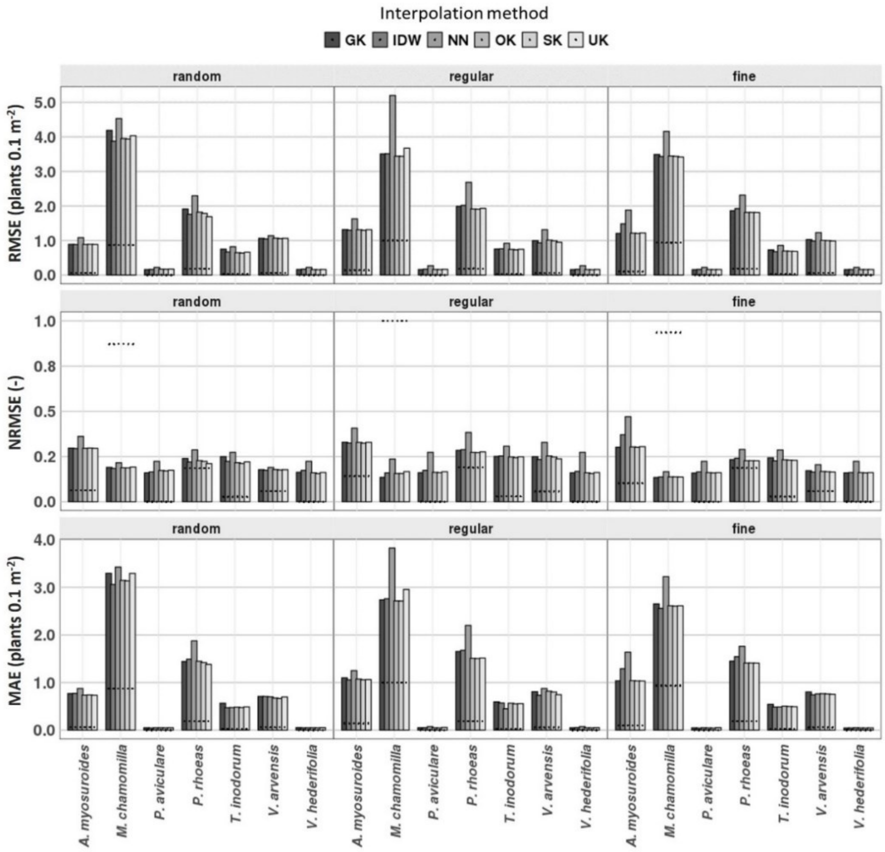

Figure 2.6: Validation results for field 3 and the three grid types (random, regular, and fine). The RMSE, NRMSE, and MAE between observed and predicted values with six different interpolation methods – Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary

Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK) – are shown. The dots show the normalized mean weed density observed in the grid sampling.

Field 4

The mean NRMSE for all species observed in field 4 was almost twice as high for the regular grid (0.41) than for the fine (0.21) and random grid (0.21; Figure 2.7). The RMSE was similar for the fine (0.98) and the random grid (1.00) and slightly lower for the regular grid (0.91). The correlation coefficient between the mean MAE of all methods and the mean species number was close to zero. To compare the NRMSE between the species, a mean NRMSE of all interpolation methods was calculated. The species with the highest NRMSE for the fine grid were *P. aviculare* (0.24) and *Matricaria* spp. (0.24). For the random grid, *Matricaria* spp. were the species with the highest NRMSE (0.26) and the species *V. arvensis* for the regular grid (0.51). The NRMSE of *V. arvensis* for the random (0.19) and fine grid (0.18) was less than the half of the NRMSE of the regular grid. While the *PI* is higher than one for the fine and random, it is less than one for the regular grid. The weed species with the lowest NRMSE for the random and regular grid was the species with the lowest occurrence (*Cirsium arvense* (L.) Scopoli) and the species *V. arvensis* for the fine grid. Comparing the interpolation methods, the NRMSE for all weed species and grid types was highest for NN (0.33), similar to the other field results. The NRMSE for the other interpolation methods was similar: 0.24 for GK, IDW, and UK and 0.23 for OK and SK.

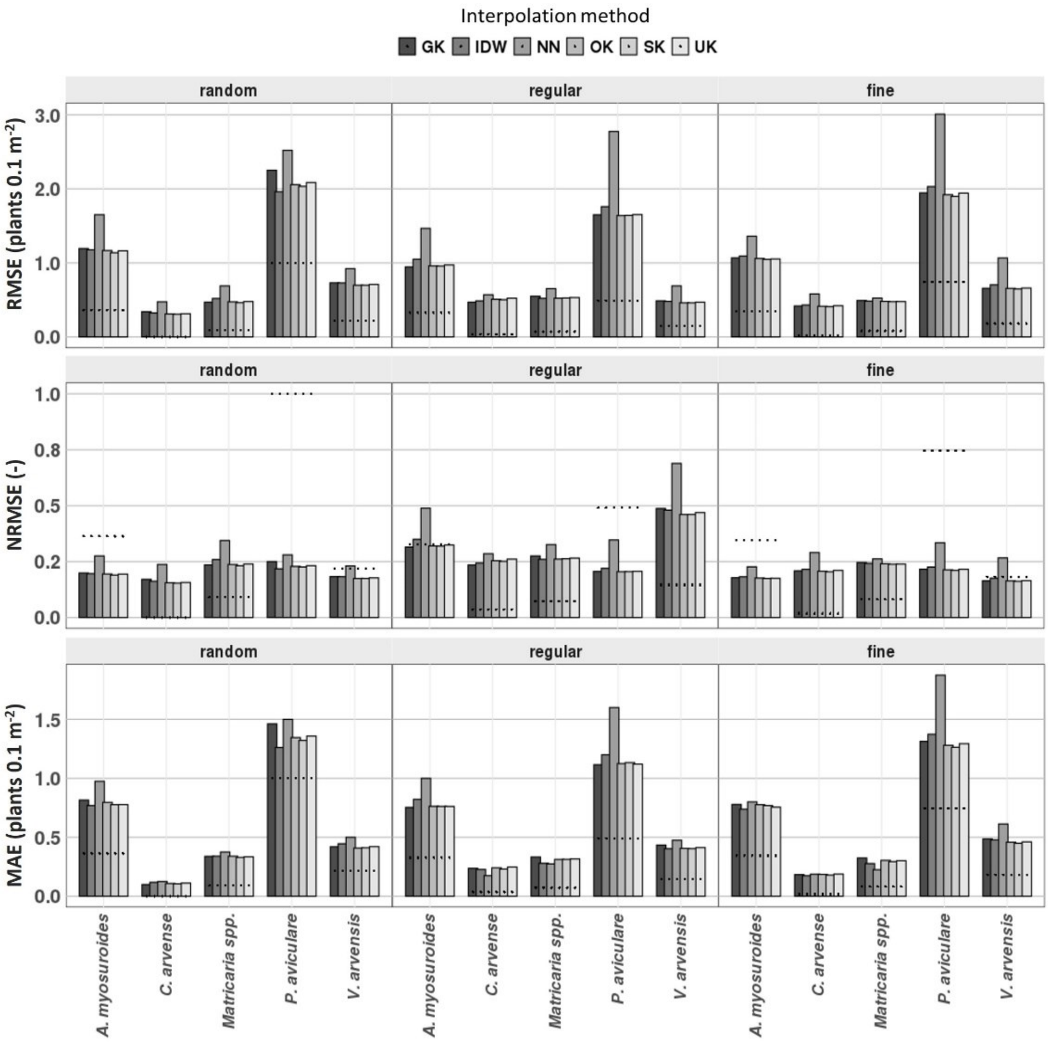

Figure 2.7: Validation results for field 4 and the three grid types (random, regular, and fine). The RMSE, NRMSE, and MAE between observed and predicted values with six different interpolation methods – Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK) – are shown. The dots show the normalized mean weed density observed in the grid sampling.

2.4.2. Selected Species

Different distributions of individual species across the field can affect the quality of prediction. To directly compare the results for the different weed distribution in each field, the NRMSE values for *A. myosuroides* and *V. arvensis* were plotted in each field and for each grid type (Figure 2.8). Also, the normalized mean weed number per 0.1 m^2 observed in the manual weed assessment was added. For both species and all study fields, the NRMSE was highest for the regular grid, especially when predicted with the NN interpolation method. Overall, the NN interpolator showed higher error values than the other interpolation methods.

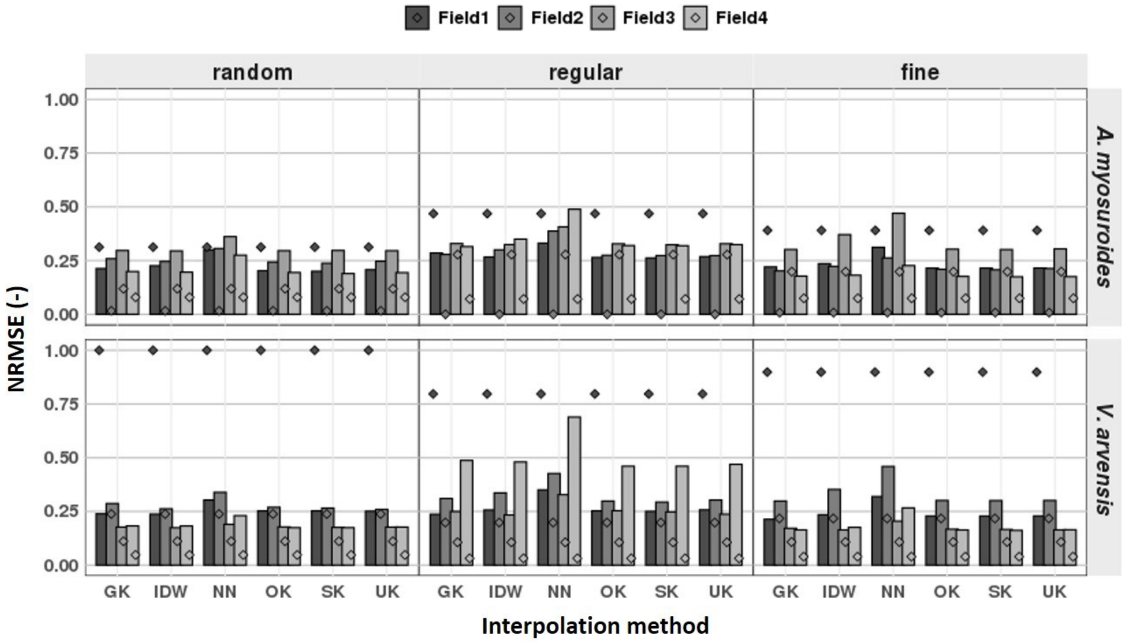

Figure 2.8: The NRMSE between predicted and observed weed numbers for the species *A. myosuroides* and *V. arvensis*. Six different interpolation methods – Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK) – were tested for four different fields. The dots show the normalized mean weed density observed in the grid sampling.

Prediction Quality Based on Weed Occurrence and Patchiness

The quality of the interpolation described by the NRMSE depends on the distribution of the weeds. Therefore, the NRMSE was compared with the *PI* and the weed density, using the Pearson correlation coefficient. The correlation coefficient between the mean weed density and the mean NRMSE for all interpolation methods did not exceeded a value of 0.37 (field 1; fine grid) for each grid type and was close to zero over all fields and grids.

Most weeds occurred in patches, except the species with an occurrence less than two plants per 0.1 m^2 in the entire field (Table S1). For all data (weed species, grid types, and fields) around 74% of the species had a *PI* higher than one with a range from 1.1 (*P. annua*; field 2; fine grid) to 26.7 (*L. purpureum*; field 2; regular grid). If only the species *V. arvensis* is considered, the correlation between the degree of patchiness and the total number of weeds is 0.73. The mean density of *A. myosuroides,* the second species observed on each studied field, did not correlate significantly with *PI*. No significant correlation between the *PI* and the mean value of NRMSE for all species, fields and grid types was observed.

Prediction Quality for Minimum and Maximum Weed Densities

The weed distribution maps (Figure 2.3, Figure S1–Figure S3) suggested that the Kriging methods smooth the weed numbers and accordingly do not predict maxima and minima resp. weed-free areas. To investigate this, the grid points were compared without any weed occurrence (less than 0.5 plants 0.1 m^{-2}) in relation to the total observation points (%) and maximum weed densities (plants 0.1 m^{-2}) based on the observed values of each grid point and compared them to the corresponding predicted values (Table 2.2). The maximum and weed-free values are derived from the mean of the species for each grid type. Table 2.2 shows that the NN method depicts the maximum weed number most similar to the observed maximum plant density. For the other methods, the values for the maximum are predicted to be lower than they were observed. For the field 1, 2, and 4 all Kriging methods predict a maximum weed density that was less than the half of the actual value. The maximum values predicted are higher than those of Kriging and lower than those of NN. The percentage weed-free area shows the smallest deviation between the measured and predicted values using the UK method; the highest difference were observed using OK and NN.

Table 2.2: Actual and predicted maximum weed number at the grid points (plants 0.1 m^{-2}) and weed-free grid points (%) for the four study fields with three different grid types (random, regular, and fine). The predicted values are based on six different interpolation methods: Gaussian copula Kriging (GK), Inverse Distance Weighting (IDW), Nearest Neighbor (NN), Ordinary Kriging (OK), Simple Kriging (SK), and Universal Kriging (UK).

		Maximum (weed no. 0.1 m^{-2})							Weed-free grid points in %						
			estimated							estimated					
		actual	GK	IDW	NN	OK	SK	UK	**actual**	GK	IDW	NN	OK	SK	UK
Field 1	random	**4.3**	1.8	2.5	4.1	1.8	1.8	1.9	**69.0**	67.0	65.5	64.5	64.3	63.5	69.0
	regular	**4.5**	1.7	1.9	3.5	1.9	1.9	1.9	**70.5**	66.5	66.5	62.5	63.8	66.0	73.0
	fine	**5.3**	1.8	2.9	4.9	2.2	2.2	2.2	**69.8**	59.6	64.8	63.1	63.5	64.8	69.0
Field 2	random	**4.9**	2.4	3.3	4.7	2.4	2.4	2.4	**74.0**	67.7	66.8	66.5	66.2	66.9	73.1
	regular	**5.8**	2.4	3.4	5.8	2.8	2.8	2.9	**69.3**	67.6	56.0	55.0	55.0	53.7	69.3
	fine	**6.4**	1.5	4.0	5.6	2.0	1.9	2.1	**71.6**	44.0	55.0	49.2	49.8	50.4	71.9
Field 3	random	**6.3**	3.6	4.0	5.9	3.5	3.5	3.6	**55.0**	45.7	47.5	45.7	45.7	44.6	53.9
	regular	**6.4**	3.7	4.1	6.0	3.7	3.8	3.9	**51.8**	47.5	45.4	39.3	39.3	43.2	48.9
	fine	**7.0**	3.9	4.3	6.6	3.9	3.9	4.0	**53.4**	44.3	45.9	42.3	42.1	43.8	54.3
Field 4	random	**4.6**	1.6	2.4	4.6	1.3	1.3	1.3	**72.5**	60.0	66.0	53.5	53.5	63.0	71.0
	regular	**3.2**	0.6	1.1	3.2	0.7	0.7	0.8	**79.0**	60.5	72.5	69.5	69.0	72.5	81.5
	fine	**4.6**	0.8	2.1	4.6	1.2	1.1	1.2	**75.8**	67.0	70.8	62.0	61.8	68.5	76.8

2.5. Discussion

To implement site-specific weed management (SSWM), weed distribution maps are required. Knowing the spatial distribution and densities of different weed species across the field allows for spatially adapted weed management strategies. As part of this study, three sampling grids with different grid point numbers, arrangements, resolutions, and six interpolation methods were tested to determine which combination of grid type and interpolation method yields the most accurate estimation of weed distribution.

2.5.1. Prediction Quality of the Different Interpolation Methods

On arable fields, areas with high weed densities can coexist with areas without any weed infestation. To serve as a basis for SSWM, an interpolation method must provide accurate, species-specific predictions of weed densities for different weed infestation levels and distribution patterns. A frequently used interpolation method for creating weed distribution maps is Inverse Distance Weighting (IDW), which predicts weed numbers based on the distance between the estimated and the sampled grid points (Kolářová and Hamouz, 2016; Martín et al., 2015). In this study, the weed distributions prediction with IDW resulted in slightly higher error terms than the predictions with the Kriging interpolators. In other studies, similar results were achieved when comparing IDW and Kriging for interpolation of weed distribution (Dille et al., 2003). The Simple (SK) and Ordinary Kriging (OK) resulted in the lowest Normalized Root Mean Square Error (NRMSE), even though the difference in the NRMSE values of the other Kriging methods was minor. The study, six interpolation methods were tested regarding their prediction quality. Another option to further evolve the interpolation quality is to use multivariate geostatistics and to integrate further variables describing the location, such as soil or farming management parameters (Pätzold et al., 2020).

Similar to the results of other studies, especially the Kriging methods smoothed the weed densities across the area, resulting in predictions of lower maximum and higher minimum weed densities for the study fields when compared to the actual measured weed densities (Dille et al., 2003; Hamouz et al., 2006; Rew et al., 2001). Kriging relies on the assumption of stationarity and linearity, meaning that the spatial distribution of the variable is constant and linear across the entire study area. If the spatial structure of the weed distribution is not constant, as for most weed species, this can lead to inaccuracies in predicting weed densities. An underestimation of the actual weed densities, as it was the case with Kriging methods in this study, can be critical, especially if weed control decisions are based on fixed weed control threshold levels (Backes and Plümer, 2003). If weed densities lower than the actual densities are predicted, threshold are not exceeded and thus no weed control treatment is conducted on areas requiring control. The only method that could accurately estimate the maximum weed density values in this study was the Nearest Neighbor (NN) method. This is attributed to the simplified approach of associating the value of the grid point based on the surrounding sampled values, thus avoiding smoothing. However, this method is highly simplified and resulted in the highest mean errors (Figure 2.4 – Figure 2.7). Finding a way to combine the strength of the NN method (less smoothing) with interpolation methods with lower error values in prediction, like Kriging, could be interesting for future studies.

As a result of smoothing of the weed distribution over the area, all interpolation methods also predicted weeds in areas where no weeds were observed during grid point sampling. The method that could most accurately estimate the weed-free grid points in the study was the UK method, while OK and NN resulted in the highest mean errors. Even though the smoothing effect is well studied for kriging, its impact on the practical implementation of SSWM is not widely discussed. An overestimation of the weed densities can be a problem for the application of SSWM approaches as weed management may be indicated on areas where no weeds are actual present (Zanin et al., 1998). On the contrary, the weed density might also be underestimated resulting in insufficient control in some area. Especially for species like *G. aparine* with a high competitive ability and therefore a low economic control threshold value of 0.1–0.5 plants m^{-2}, the smoothing effect can lead to a high risk of yield loss. However, for SSWM using fixed weed control thresholds values, an underestimation of weed densities is more critical than an overestimation (Rew et al., 2001). Even though the smoothing effect is inherent to the application of interpolation methods based on a weighted average (Yamamoto, 2005), the IDW method smoothed the weed densities to a lesser extent than the Kriging method. A higher performance in predicting maximum and minimum density values was expected for interpolation based on the Gaussian copula (GK) method as shown in a study by Atalay and Tercan (2017). This method is expected to better perform on non-normally distributed data by separating the marginal distributions from the dependency structures (Han and Oliveira, 2018). However, the results of this study did not confirm an outperformance of the GK method as the weed densities were similarly smoothed. In addition, due to its higher complexity, the GK method requires much stronger computing power, which may restrict its use. Instead of using fixed economic control thresholds, a novel approach by Schatke et al. (2024) is less strongly limited by the smoothing effect and uses species-specific weed distribution maps for management decisions based on the competitive traits and ecosystem services of the weeds present in the field. Nevertheless, the accuracy of weed distribution maps is decisive for all methods deriving management maps based on weed distribution.

2.5.2. Species-Specific Prediction Quality

All weed species in the four study fields showed different levels of patchiness and densities. A study by Rew et al. (2001) pointed out that for varying weed densities, performance tests for interpolation methods are necessary, especially in fields with low weed occurrence. In this study, several weed species were observed with low plant numbers and frequencies. *Papaver rhoeas*, for example, was only observed in field 3 with one individual plant at one grid point for the random and regular grid type, respectively. To investigate whether the performance of the interpolation methods is dependent on species-specific densities, the correlation between the weed density per species and grid point and the NRMSE were examined. Even though the observed weed species did not show a similar distribution across the four experimental fields, no clear relationship was shown between weed densities and the NRMSE for all species, fields, and raster types. By calculating the mean difference between observed and estimated values (MAE), Dille et al. (2003) found that the level of precision of the tested interpolation methods was very poor for weed species with low infestation levels. For the study fields 1 and 3 with the highest weed occurrence, the correlation between mean weed density and MAE was significant (> 0.94). In contrast to the MAE, the NRMSE relates the error metric to the range of individual plant numbers per species, allowing for more accuracy in interpolation performance assessments. Accordingly, the NRMSE offers better comparability of predictions for different species. In this study, a lower weed density did not generally result in higher NRMSE. In addition, most weeds occurred in patches, except for the species with an occurrence of less than two plants per 0.1 m^2 in the entire field. No significant correlation between the index of Patchiness (*PI*) and the mean value of NRMSE of all fields and grid types for all species was observed. The weed species observed during the study are typical species for winter wheat, so the extrapolation to other crops with potential different weed species and weed distribution patterns needs to be further evaluated. However, as the distribution of the weeds in our trials cover a large part of the gradient of weed distribution between patchy and even distribution and the principal distribution patterns are the same in all crops we do not expect a significant effect of the crops on the interpolation quality.

2.5.3. Prediction Quality Based on Different Sampling Grid Distribution

As observed in the studies of Dille et al. (2003) and Hamouz et al. (2006), the difference between the Kriging and IDW methods was of lower importance for the estimation results than the selection of the spatial grid design. Even though the focus in many studies was on the distance between sampling grid points (Camicia et al., 2015; Hamouz et al., 2006; Hamouz and Hamouzová, 2022; LaMastus and Shaw, 2005), this study showed that the spatial arrangement of the grid points in the field may also have an impact on the interpolation prediction quality. For fields 1–3, there were only small differences between the three different grid types regarding the prediction qualities of the interpolation methods. However, for field 4, the mean NRMSE (0.41) of all species and interpolation methods for the regular grid was almost twice as large as for the two other grid types. Especially the species *Viola arvensis* showed a significantly higher NRMSE in the regular grid. This could be related to the fact that this species did not show a patchy occurrence when sampled by the regular grid, unlike in the two other grid types. The NRMSE did also differ significantly between the grid types for *Sisymbrium officinale* in field 1. Just as *V. arvensis*, *S. officinale* was not observed to occur in patches when observed by the regular grid while *S. officinale* patches were detected by the random and fine grid. The species *S. officinale* therefore showed higher NRMSE values in the regular compared to the random and fine grid. Even though the mean difference in interpolation performance between the grid types was smaller for fields 1, 2, and 3 than for field 4, the NRMSE was on average highest for the regular grid. When employing an equal number of grid points, these results suggest that a weed assessment on randomly distributed grid points may better represent the distribution of weeds in the field than a grid based on regular distributed grid points. Similar to other studies (Hamouz and Hamouzová, 2022; Rew et al., 2001), the spatial grid resolution also had an impact on the quality of the interpolation outcome. However, in this study, the fine grid with 80 grid points was only superior to the random grid with 40 grid points for two out of four fields. Thus for an efficient grid arrangement, a random distribution of a lower number of grid points seems to yield similar results compared to a higher number of grid points. This observation is confirmed in a study by Colbach et al. (2000) in which different random grid arrangements were tested on simulated weed distributions. For a small number of sampling points, an entirely randomly distribution of points was best for estimating mean plant densities while adding a minimal distances between sampling points to limit dependence between samples lead to better results for a higher number of samples. In this study, the visual differences in the distribution of *Polygonum aviculare* and *P. rhoeas* between the random and regular grid of field 1 showed, that not all weed patches were observed in both grid types and have a higher possibility to become visible in their composition in the fine grid (Figure 2.4). Accordingly, the risk of overlooking a weed cluster increases with increasing grid spacing.

2.6. Conclusion

The use of spatially distributed grid points for in-field weed density assessments with subsequent application of interpolation methods enables significant cost and time savings compared to a full-area weed monitoring. However, for relying on weed distribution maps for SSWM, the predictions of the interpolation must be as precise as possible. When comparing all three grid designs, the fine grid in combination with the Kriging interpolation methods provided the best representation of weed distribution and density for the majority of weed species and fields in this study. For weed species with very low occurrence, the use of interpolation methods did not result in precise prediction of the weed distribution as the mean absolute error for these species was mostly higher than the observed plant number. By smoothing the weed distribution over the area, interpolations methods frequently over- and underestimated actual weed densities in the field. This can be critical for SSWM approaches where management would be performed selectively on areas where no weeds are present. On the other hand, an underestimation of actual weed densities can be problematic when applying fixed weed control thresholds for management decisions. The approach 'Gaussian copula Kriging' did not result in less smoothing compared to the other interpolation methods. In the future, an automatic and reliable detection and classification of weeds on the species level by e.g. Unmanned Aerial Vehicles and Artificial Intelligence could significantly simplify the process of assessing in-field weed densities in high resolution and could improve the prediction quality of interpolation methods by increasing the sampling interval.

2.7. Acknowledgements

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3. From Unwanted to Wanted: Blending Functional Weed Traits into Weed Distribution Maps

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3.1. Abstract

Site-specific weed management (SSWM) is increasingly employed to reduce herbicide inputs. Incorporating functional traits of weed species allows for the selection of SSWM methods that effectively reduce the abundance of weeds with a high competitive potential (disservice) while preserving weeds that provide beneficial ecosystem services (service). In this study, we aim to assess relevant weed functional traits and translate this information into a spatial trait distribution map for weed (dis-)service provision. The distribution of weed abundance in a field was recorded using a spatial grid. Data on functional traits for the recorded weed species were extracted from published datasets and combined into the two variables, service and disservice. Individual traits (service/disservice) were weighted for each pixel of the weed distribution map based on the number of individual plants per species. Principal component analysis was employed to generate independent variables to describe the potential for service and disservice provision. As a result, two (dis-)service trait-based distribution maps were generated: one highlights field areas that provide enhanced ecological services, while the other displays areas with a high disservice potential. The results show that around 61% of the area in the field had a high service potential. The area with a high disservice was slightly higher than the half of the area with a high service, while about 32% of the field has both high service and disservice potential in the same area. This study presents a spatially explicit approach to incorporate information on weed functional traits into SSWM approaches targeted at reducing weed competition while at the same time enhancing weed functional diversity.

Keywords: biodiversity, disservice, PCA, service, site-specific weed management, weed distribution maps

3.2. Introduction

An intensification of farming practices accompanied by simplification of crop rotations, increased nitrogen fertilization rates and weed control by highly effective herbicides have been identified as potential reasons for the drastic decline in the diversity of weeds and an increase in homogenisation of vegetation communities in recent decades (Storkey et al., 2012). A study from Northern France reported a 42% decline in the number of weed species per field and a 67% decrease in the mean species density per field between surveys conducted in the 1970s and the 2000s (Fried et al., 2012).

In an agricultural context, weeds are often perceived as harmful because they compete with the crop for resources, such as light, water and nutrients. In addition to a potential yield reduction, the presence of weeds can also favour an increased abundance of crop pests (Oerke, 2006). Besides their negative competitive impact, weeds take an important role in agroecosystems by offering food resources and habitat for small vertebrate and invertebrate animals, such as rodents, insects and birds (Marshall et al., 2003) and by reducing soil erosion (Ruiz-Colmenero et al., 2013). There is evidence that the decline in weed species number can be linked to the significant observed reductions in populations and ranges of farmland birds and invertebrates. Weeds can also support crop production, for example, by maintaining and supporting pollinators (Bretagnolle and Gaba, 2015). Individual weed species are known to differ in terms of providing important ecosystem functions (Storkey, 2006) as well as in their impediment to crop production (Storkey and Westbury, 2007). It is therefore important to recognise that weeds hold conservation value, and sustainable weed management should consider their coexistence with the crop for promoting their biodiversity benefits.

The global human population is projected to reach 9 billion by 2050, resulting in a significant increase in food consumption and demand (The Royal Society of London, 2009). To achieve sustainable agricultural intensification while minimising inputs and reducing environmental impact, innovative weed management strategies are essential. The goal of creating more sustainable weed control systems that incorporate the diversity of the weed community in arable fields is complemented by trends in policy to promote biodiversity in agroecosystems while also enhancing agricultural productivity (Maskell et al., 2020). In most conventional cropping systems, weed management still relies on the application of broad-spectrum herbicides that control a wide range of plant species. However, the increasing concern about the environmental impacts of herbicides, rising prices of crop protection products and policy restrictions, such as the European Green Deal, have strengthened the development of more targeted and sustainable weed control approaches. One of these approaches is site-specific weed management (SSWM) where weed control is tailored to the spatial distribution of weeds at a given site and which aims at reducing the environmental and economic impacts of weed control measures (Gerhards et al., 2022). The potential of SSWM for herbicide reduction has been demonstrated for different cropping situations for several decades. In a 2-year study, SSWM showed herbicide savings ranging from 6% in maize to 98% in winter barley without enhanced weed control costs in subsequent years (Gerhards and Oebel, 2006). A 5-year field experiment observed a significant reduction of 54% in herbicide usage by employing SSWM (Timmermann et al., 2003). Overall, the results of SSWM showed a high herbicide saving potential by more precisely targeting the spatial distribution of weeds.

For every SSWM approach, the detection of weeds and their spatial distribution in the field is essential. Recent innovative approaches facilitate an automatic weed detection at the species level by technologies including 3D cameras, multispectral imaging combined with artificial intelligence (AI) for weed classification and computer based decision algorithms (Hasan et al., 2021; Wu et al., 2021). A study using unmanned aerial vehicle (UAV) to automatically detect the plants outside of the corn row and classify them as weeds, leave 26% of the acreage untreated with herbicide (Sapkota et al., 2023). Further, species-specific weed detection allows for species-specific SSWM approaches incorporating the spatial distribution of single species or weed functional groups. A German study tested the application of SSWM using control thresholds for functional groups of weeds and a GNSS-guided multiple-tank sprayer in comparison to using a single tank mix targeting all present weed species (Gutjahr et al., 2012). The use of control thresholds for functional group of weeds resulted in an area untreated with herbicides of 59%–80% whereas using a single tank mix targeting all three groups resulted in an untreated area of 37% (Gutjahr et al., 2012). Despite a presumably higher herbicide saving potential, to our knowledge, current decisions in SSWM are not made at the weed species level. This can be mainly attributed to the high effort of a manual weed sampling and the expertise needed for identifying the weed species.

Automated image-based species identification is a promising avenue that has been discussed since the potential of machine learning for ecological applications became apparent (Christin et al., 2018). With the advent of deep learning methods, automatic species identification is achieving accuracy comparable to that of human experts (Wäldchen and Mäder, 2018).

Automatic detection of weed species is particularly challenging, as they need to be detected at early stages of development for most weed control approaches. As weed-detection technologies have only been tested in a limited number of experiments with a small number of weed species, there is little research on automatic identification and precise spatial positioning of plants and weeds in a practical field environment (Hasan et al., 2021). It is expected that fully automatic identification and location at the species level will be feasible in the near future. Therefore, it is crucial to explore how the knowledge gained from species-level weed detection can be effectively incorporated into sustainable and environmentally friendly weed management concepts.

When weed management approaches are tailored to the individual weed species present in a field, the decision on whether or not weeds need to be controlled is often based on established weed (economic) control thresholds. These thresholds are usually calculated based on potential crop yield and quality reduction, mainly by incorporating economic losses linked to the weed population densities, and disregarding the biological characteristics of the species (Gerowitt and Heitefuss, 1990). However, a greater research effort to determine the negative and positive impacts of weeds in agroecosystems is needed to optimise both crop production and environmental integrity while preserving weeds' role in the ecosystem (Neve et al., 2018). Studies focusing on the functional traits of weeds have therefore gained popularity in recent decades. Most studies focus on identifying and analysing the functional traits of weeds rather than integrating them into weed management concepts. For example, by analysing functional groups in the United Kingdom arable flora that can help assess a weed community in the context of reconciling biodiversity provision with crop production (Storkey, 2006) or how the weed trait responds to cropping regimes (Gunton et al., 2011). Currently, there is a lack of knowledge on how to use information on weed functional traits to design and implement weed control systems that allow weed diversity to be maintained in the cropping system without sacrificing crop yield level. To meet this challenge, SSWM approaches that directly address the ecological dynamics and weed control requirements of weed-crop systems in a site-specific manner by incorporating weed traits at the species level could play an important role. To our knowledge, there are currently no approaches to evaluate the functional characteristics of weeds in a field and to integrate this information into a weed management field map.

The goal of this study was to develop an approach for incorporating information on weed functional traits related to both weeds' beneficial ecological functions (‘service’) and negative impact ('disservice') into site-specific weed distribution maps. By taking into account the occurrence, distribution and functional traits of individual weed species in a crop field, we aimed to create spatially explicit field maps highlighting distinct field areas for two indicators: (a) the potential ecological service provision (service) and (b) the estimated negative impact on crop productivity (disservice). A map showing the relationship between service and disservice potential was created and could serve as the basis of the following management plan.

3.3. Materials and Methods

3.3.1. Study Field

A spatial grid with 40 grid points for manual weed assessment was installed in the centre of an experimental arable field planted with winter wheat (*Triticum aestivum* L.; variety Campesino; 350 seeds m^2, seeding date: 27 October 2021) in Sickte, north-eastern Germany (52.13029.200 N 10.37049.200 E; Figure 3.1). The grid points were 10 m apart along the wheat row and 6 m apart between the crop rows. On the plot with the grid points (approx. 24m × 100m), no herbicide treatment was carried out before weed assessment. Fertiliser, growth regulator, and fungicide applications were conducted according to common agricultural practice. A manual weed assessment was carried out on the study field in September 2021. All weed species and the number of individual plants per species were determined at each of the 40 grid points using a counting frame with an area of 0.1 m^2. Based on these data, weed distribution maps for the grid area were generated for each individual weed species using R 4.1.1 (R Core Team, 2021). Five different interpolation methods were tested (Simple Kriging, Universal Kriging, Ordinary Kriging, Inverse Distance Weighting, and Nearest Neighbour) using a Leave-One-Out Cross Validation (Supplemental material – Table S2). The method with the lowest normalised root mean square error (Simple Kriging) was used to create the weed distribution maps. The interpolated maps had a resolution of 0.1 m × 0.1 m and were aggregated to a pixel resolution of 1 m × 1 m, which fitted to the available tools for SSWM. For a total area of the experimental field of 24 m × 100 m, this results in a total pixel number of 3128 pixels with edges around the grid.

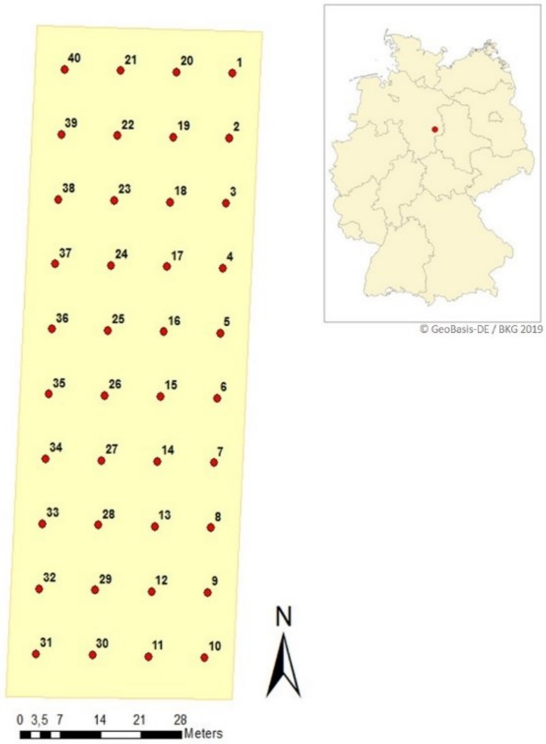

Figure 3.1: Study field in Sickte, Germany with 40 grid points for weed assessments (approx. 24 m x 100 m).

3.3.2. Selection of Functional Weed Traits

Since weed control takes place at an early growth stage when most weeds' functional traits are not measurable in the field, these traits can usually not be quantified before a weed control decision. Instead, published data have to be used to describe the future trait potential of the weed plants. Functional trait values for the observed weed species were retrieved from published literature (referred articles and books) and online sources (e.g., databases; Table S3 and Table S4). The traits were selected based on their relevance to the beneficial ecological services provided by the weed species (services) and as indicators of their competitive potential or negative impacts on crop production (disservices). For all traits (service and disservice), a high trait value was linked to a high service and disservice potential of the weed species. As the trait expression for a weed species can vary significantly (Perronne et al., 2014), the use of a specific trait value for a species covers only a mean expression and not the possible variations in the field.

Service Traits

Nine different functional traits were used to describe the beneficial ecological functions of weeds (service traits, Table S3). The first traits were collected by Marshall et al. (2003): number of insect families recorded on individual weed species (insect number), the number of insect species recorded on individual weed species (insect species) and the number of insect species that are dependent to the weeds species to complete their life cycle (host specific insects). Further service traits were the number of links between the individual weed species and natural enemies of arthropods (natural enemies), phytophagous arthropods (phytophages) and pollinators (pollinators) retrieved from Bosch et al. (2022). The links to the species can be traced back to the provision of a food source or host by the weeds to the different groups. The trait 'birds direct' includes birds that directly feed on the weed plant and 'birds indirect' linkages include birds of prey that feed on birds directly associated with the individual weed plant. The service trait 'flower duration' represents the duration of the flowering in months and thus the duration of pollen and nectar provision (Font, 2016).

Disservice Traits

The six weed traits representing the weeds' competition ability were retrieved from different sources. The economic threshold values were taken from the German Federal plant protection service of Bavaria ('economic threshold'; (LfL Bayern, 2024)). When the weed density (plants m^{-2}) of a specific weed species is above this economic threshold, controlling these weeds is estimated to result in higher economic net returns (Gerowitt and Heitefuss, 1990). The 'specific leaf area' represents a ratio between the leaf area of the fresh leaf and leaf dry mass (SLA; $mm^2\ mg^{-1}$) collected by Pakeman et al. (2015). The vegetative trait 'plant height vegetative' is the distance between the uppermost tip of photosynthetic tissue and the ground level. Further traits were 'relative growth rate of green area' in spring (RGRLs; d^{-1}) and autumn (RGRLa; d^{-1}) (Storkey, 2006) as well as the number of observed links between the weed species and pest arthropods ('pest species') (Bosch et al., 2022).

3.3.3. Analysis

To compare the trait values within the groups of service traits (Table 3.1) and disservice traits (Table 3.2), respectively, we normalised trait values between zero and one. The highest value for the respective trait received a value of one and the lowest trait value received a value of zero. Trait values in between were determined accordingly. This resulted in a relative measure of the traits for the specific weed species composition on the respective field site. There is an exception for the 'economic threshold' trait: a low threshold value indicates a high competitive ability of the weed species. For the normalised trait values, the highest value from the published study gets a zero and the lowest a one.

To weight the traits based on the spatial abundance and density of the weed species in the weed distribution map, the weed number per pixel was multiplied with the normalised specific trait value (Equation 3.1):

$$WT_i = \frac{\sum(N_{s_i} \times T_S)}{\sum No.Weeds_i} \tag{3.1}$$

The weighted trait WT at each pixel i of the weed distribution map was determined for all services and disservices separately. First, the sum of the number of each species N_{S_i} at the pixel i multiplied with the trait value T for each species S was calculated. This value was divided by the number of individual plants of all weed species occurred at the pixel i. The result is a new trait distribution map for each weighted trait.

To further condense the nine service trait distribution maps and seven trait disservice distribution maps, we used a principal component analysis (PCA). PCA is chosen due to the hierarchical assignment of effects on service and disservice is essential to weight the influence of each trait value. One time on the trait distribution maps for service potential and one time for the trait distribution maps for disservice potential. The outcome were two spatial field maps, the disservice distribution map and the service distribution map. All analyzes were conducted using R 4.1.1 (R Core Team, 2021). The PCA was done using the RStoolbox package (Müller et al., 2022). The 'rasterPCA' function takes raster objects as input. The output of the function is a new raster object containing the principal component scores for each pixel of the field map. The values of the first principal component were used to create (dis-)service distribution maps.

To analyze the ratio between disservice and service in the study field based on the generated (dis-)service distribution maps, a correlation analysis using the values of the first PCA axis for each pixel was conducted, Spearman's correlation coefficient was determined and a scatterplot was generated. A correlation coefficient of 1 indicated a high spatial conflict between service and disservice potential on the study field, while a value of −1 indicated none. The pixel values (principal component scores from the PCA) of the (dis-)service distribution maps, which rated from approx. −1 to 1, were converted into service and disservice potentials from 0% to 100%. A service potential of 100%, the highest possible potential for provision of beneficial ecological services based on the employed functional traits and the weed species present on the field was assumed. Afterwards, the scatterplot was divided into four quadrants (Q1–Q4) based on two hypothetical thresholds of 50% service and disservice potential. The 'Q1' shows pixel values with a disservice potential >50% and service potential <50%. 'Q2' includes pixel values with a service and disservice potential >50%. The 'Q3' includes pixel values with service and disservice potential <50% and in 'Q4' the service was >50% and disservice <50%.

3.4. Results

The overall weed species recorded during the weed assessment were *Myosotis arvensis* H., *Poa annua* L., *Polygonum aviculare* L., *Stellaria media* L. Ville and *Viola arvensis* Murr (Figure 3.2). The most frequent and abundant weed species was *P. aviculare* with hotspots of high occurrence (>100 individuals m^{-2}) at grid points #9 and #32. *V. arvensis* was the second most frequent species, especially at point #37 with around 70 individual plants per m^2. The occurrence of *Poa annua* at the sampled grid points was very low (<30 individuals m^{-2}) whereas *M. arvensis* and *S. media* showed intermediate densities. *M. arvensis* occurred with a higher abundance in the western part of the field and *S. media* in the northern part. All species, except for the least observed species *Poa annua*, were distributed in patches with hotspots in different parts of the field. No consistent abundance pattern between the species was noticeable.

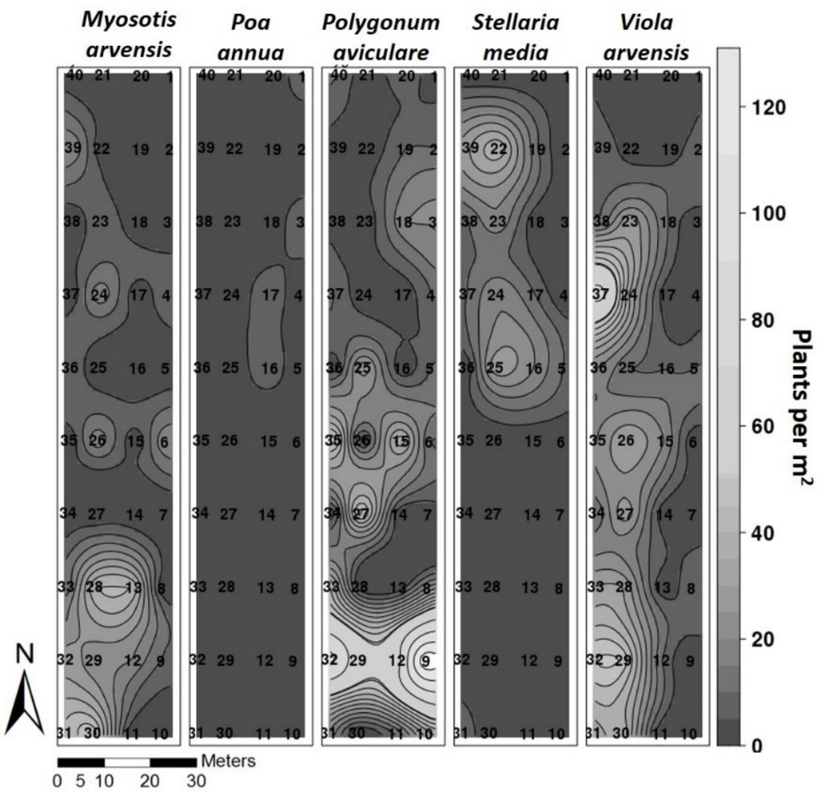

Figure 3.2: Weed distribution maps (number of individual plants m^{-2}) for the weed species observed at the study site.

According to the trait analysis, the species *Poa annua* and *P. aviculare* showed the highest number of linkages with insect families (Table 3.1). In addition, *Poa annua* had the highest values for the traits host specific insects, phytophagous insects and, together with the weed species *S. media*, the highest value for the trait flowering duration. The highest values for the traits pollinators and indirect birds were observed for *P. aviculare. S. media* showed the highest value for four traits: insect species, natural enemies, direct birds and flowering duration. The values for the service traits ‘insect families’, ‘insect species’, ‘host specific insects’, ‘phytophages’, ‘pollinators’, ‘birds indirect’ and ‘flowering duration’ for the weed species *M. arvensis* and *V. arvensis* were lower than for the other three species. For the ‘natural enemies’ the species *P. aviculare* and *V. arvensis* showed the lowest values and for ‘birds direct’ the species *Poa annua* and *M. arvensis*.

Table 3.1: Normalised values for the collected service traits (see Table S3 for description of traits).

Species	Insect families	Insect species	Host-specific insects	Natural enemies	Phytophages	Pollinators	Birds (direct)	Birds (indirect)	Flowering duration
M. arvensis	0.08	0.01	0.00	0.40	0.00	0.00	0.07	0.00	0.00
P. annua	1.00	0.74	1.00	0.20	1.00	0.53	0.00	0.33	1.00
P. aviculare	1.00	0.86	0.57	0.00	0.91	1.00	0.20	1.00	0.17
S. media	0.77	1.00	0.57	1.00	0.70	0.47	1.00	0.33	1.00
V. arvensis	0.00	0.00	0.00	0.00	0.19	0.06	0.47	0.00	0.17

The species *Poa annua* had the highest SLA and the highest number of linkages with pest species (Table 3.2). *S. media* had the highest RGRL for autumn and spring. *V. arvensis* had the highest economic threshold value, and *M. arvensis* and *Poa annua* had the lowest economic threshold value. In addition, *V. arvensis* showed the highest value for the trait vegetative plant height. *M. arvensis* had the lowest linkages with pest species and a low economic threshold value.

Table 3.2: Normalized values for the collected disservice traits (see Table S4 for description of traits).

Species	Economic threshold	SLA	Plant height vegetative	RGRLa	RGRLs	Pest species
M. arvensis	0.00	0.14	0.63	0.54	0.64	0.00
P. annua	0.25	1.00	0.00	0.65	0.74	1.00
P. aviculare	0.50	0.00	0.64	0.53	0.74	0.28
S. media	0.75	0.40	0.63	1.00	1.00	0.16
V. arvensis	1.00	0.13	1.00	0.00	0.00	0.13

In the first step of creating the final (dis-)service distribution maps, weed traits were weighted based on the occurrence of weed species for each pixel of the study field. The thereby generated trait distribution maps for the service traits show the spatial pattern of service functions in the field for each service trait (Figure 3.3). Areas with a value of one have the highest influence on the service performance provided by the present weed species whereas areas with a value of zero exhibit a low service provision. The service functions of the weeds for the traits insect families, insect species, phytophages, pollinators as well as the indirectly linked birds showed a similar spatial pattern. Hotspots for the above traits were located at grid points #9 and #10. In particular, traits related to insect families, insect species, natural enemies, directly linked birds and flowering duration show very high values at and around grid point #22.

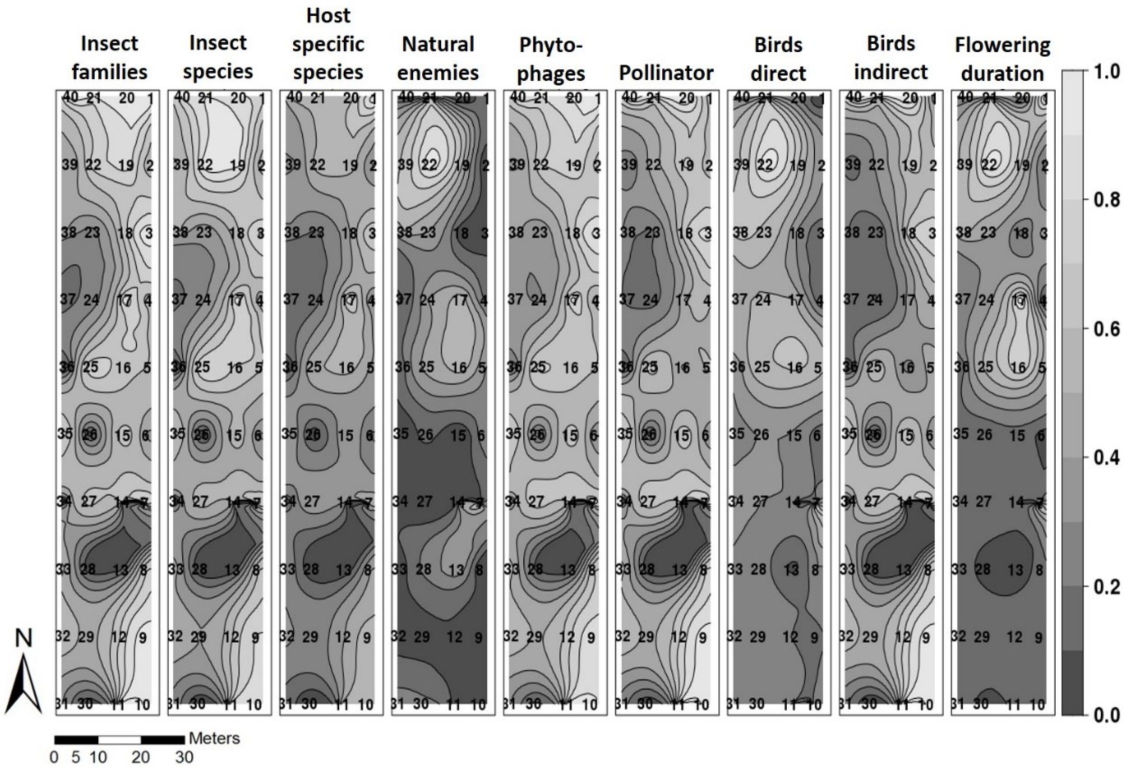

Figure 3.3: Trait distribution map for weighted values of the service traits for each grid pixel of the weed distribution map. The raster points range from #1 in the northeast to #40 in northwest.

A greater spatial heterogeneity was displayed in the distribution of the values in the trait distribution maps for the weighted disservice traits (Figure 3.4). While values for the RGRLa, RGRLs and pest species were high in the eastern part of the map, the values for the plant height vegetative and economic threshold are greater in the western part. While the economic threshold, RGRLa and RGRLs showed high values at grid point #22, the plant height vegetative and pest species showed lower values at this point. Maximum values for the plant height vegetative and economic threshold were reached at point #37.

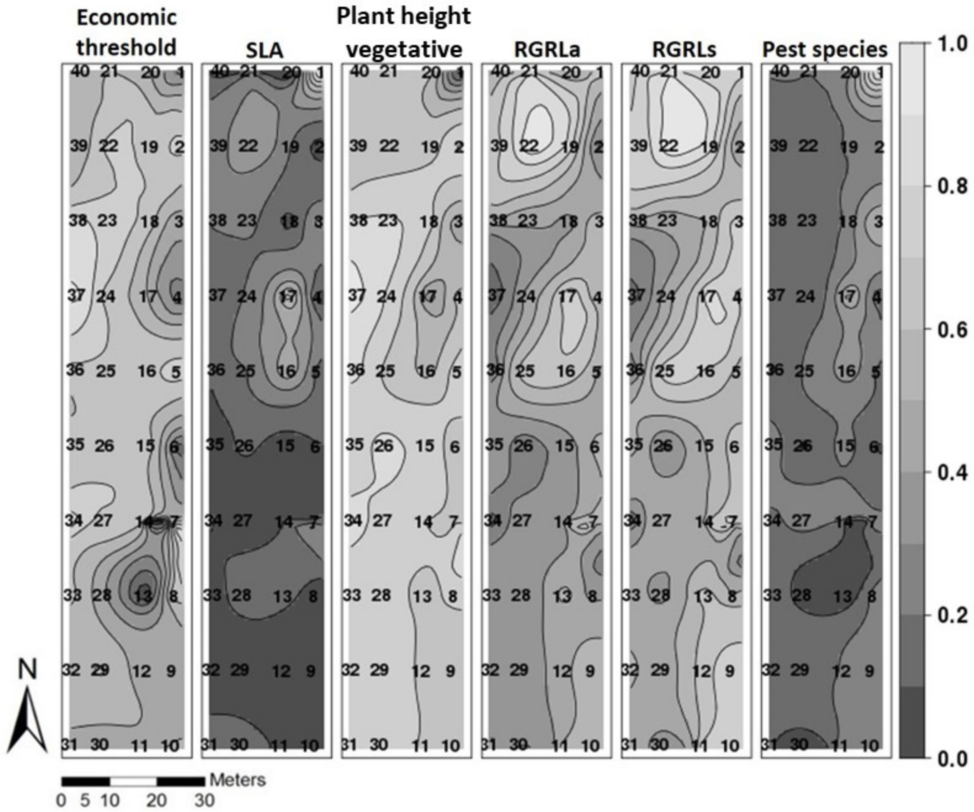

Figure 3.4: Trait distribution map for weighted values of the disservice traits for each grid pixel of the weed distribution map. The raster points range from #1 in the northeast to #40 in northwest.

To condense the information of the trait distribution maps into the two aggregated (dis-)service distribution maps, a PCA was conducted. The results indicate spatial areas in the field that exhibit a high potential for services and disservices based on the distribution of the present weed species (Figure 3.5). A high (dis-)service potential exists at a value of 1, an average one at 0 and a low one at −1. High disservice values occurred in the eastern and northern parts of the study field, while both are lower in the western part. The service values showed a similar trend: higher values in north and east, lower values in the western part of the service distribution map. The final map showed a similar spatial pattern like the traits insect families, insect species, phytophages, pollinators as well as the indirectly linked birds. In contrast, the final disservice distribution map had a similar pattern to the pest species, RGRLa and RGRLs.

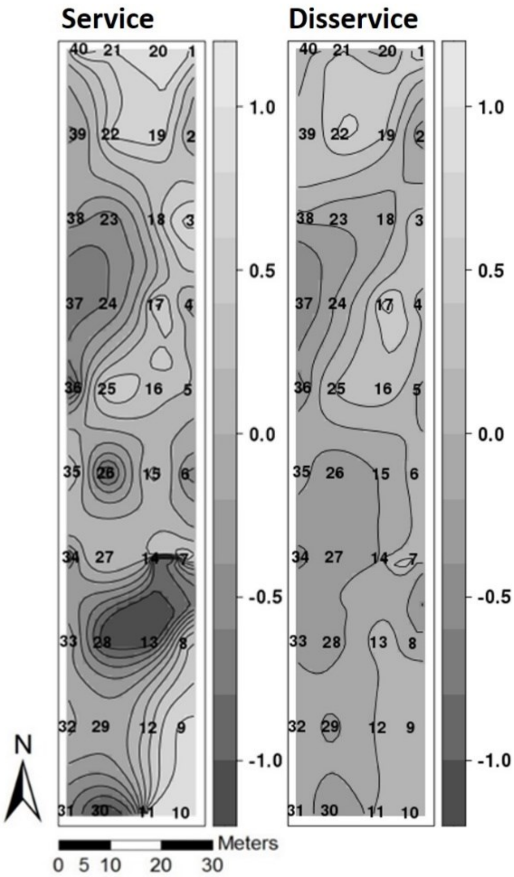

Figure 3.5: Service and disservice distribution maps in the study field showing the scores of the first axis of a PCA based on the occurrence of the weed species and the species-specific traits. The raster points range from #1 in the northeast to #40 in northwest.

The correlation analysis of the pixel values of the (dis-)service distribution maps resulted in a positive correlation coefficient of 0.71. Therefore, the area of the field that shows a similar service and disservice potential was relatively high for the study field. After dividing the scatterplot (Figure 3.6 (a)) in four quadrants (Q1–Q4) based on a threshold of 50% of the total (dis-)service potential at this study field, there are four different groups of pixel values representing the correlation between service and disservice potential. The ‘Q1’ include 74 pixel values (1 pixel = 1 m^2), ‘Q2’ includes 9997 pixels, 1161 pixels in ‘Q3’ and 896 in ‘Q4’. The pixels with opposing potential (either high service and low disservice, or the other way around) are each approx. twice the number of pixels with the same trend for both potentials. With a total size of 3128 m^2, the ‘Q1’ represents 2.4%, the ‘Q2’ 31.9%, the ‘Q3’ 37.1% and the ‘Q4’ 28.6% of the total study field. The part of the study field with a small disservice potential (<50%) was 65.7% of the total field (Q3 and Q4). Overall, 60.5% of the field showed a high service potential (>50%;

Q2 and Q4), the proportion of pixel values with a high disservice potential (Q1 and Q2) was slightly higher than the half (34.3%). While 31.9% of the field showed both a service and disservice potential greater 50%, the area with only high disservice is small (2.4%).

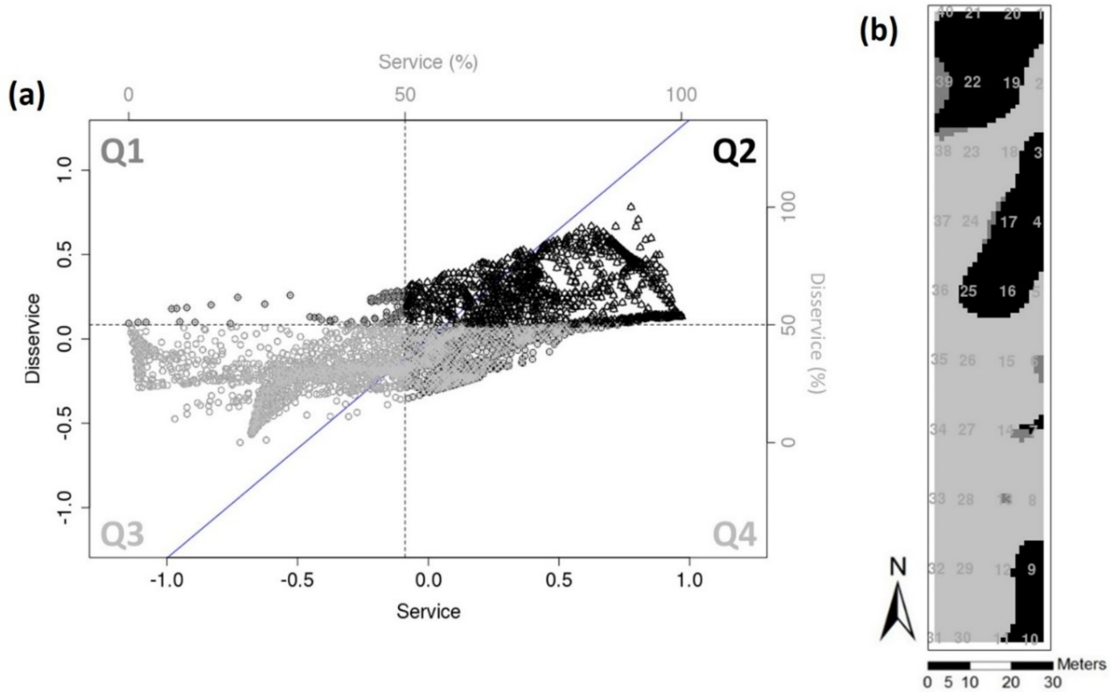

Figure 3.6: Correlation (a) between the pixel values of the service and the disservice distribution maps (Figure 3.5) with values from -1 (0% potential) to 1 (100% potential). The quadrant ‘Q1’ includes values with high disservice and low service potential, ‘Q2’ values with high service and high disservice potential and both ‘Q3’ and ‘Q4’ have a low disservice potential and therefore received the same color. (b) The ‘(dis-)service ratio field map’ was created based on the locations of the pixels in the four quadrants (a) using the same colors.

3.5. Discussion

As new technologies for in-field weed detection and recognition at the species level will be further developed and implemented, we need to design concepts and approaches on how the gained knowledge can be effectively used to design sustainable weed management systems. While weeds compete with the crop for resources, they also offer valuable ecological services such as providing habitat and food for beneficial insects. Trait-based approaches are therefore a promising way to address the challenge of designing effective and environmentally sustainable weed management strategies including both weed control and biodiversity conservation (Gaba et al., 2017).

Since the weeds are mostly in the early stages of development when a management concept is created, a survey of plant-specific traits before the application of weed management operations is not feasible. Even within a single weed species, the trait values can varying plant-specific and site-specific within an arable field. Therefore, it should be taken into account that the presented approach can be interpreted as a predictive model for the (dis-)service potential in the study field, which is based on published weed trait data and the observed weed distribution.

3.5.1. Distribution Maps of (Dis-)Service Potential in the Study Field

The results of this study show that the service function of weeds can be considered separately from their disservice ability on a spatial basis. The (dis-)service distribution maps highlight the potential of a specific field for biodiversity provision as well as crop competition by summarising the traits, species and weed densities. For our study field, the service potential was high in those parts of the field where the weed species *P. aviculare* and *S. media* occurred at high densities. The species *M. arvensis* and *V. arvensis*, on the other hand, showed a lower contribution to the service distribution map. Based on the occurrence of the weed species in our study field, the northern and eastern parts of the field had a high potential for providing ecological services.

In terms of the disservice distribution maps, the species *M. arvensis* and *S. media* had a high impact on the distribution of disservice potential in the field, with the highest impact observed in the north-eastern part. In case of our study field, the service and disservice distribution maps showed a similar spatial pattern: The parts of the field with a high disservice did exhibit a high service potential and the opposite. This visual impression is confirmed by the positive correlation coefficient calculated based on the pixel values of the (dis-)service distribution maps. The results could differ, if weed species without a balance between service and disservice is dominating on the field. Further tests on other study fields and with different weed diversity should be contributed in the future.

To enable future management decisions taking into account the (dis-)service distribution, we generated a scatterplot with the pixel values of the service and the disservice distribution map. By dividing the scatterplot into four quadrants based on a threshold of 50% service and disservice potential (Figure 3.6a), a (dis-)service ratio field map could be created (Figure 3.6b).

The map visualised the four types of quadrants that could serve as a basis of weed management decisions: The quadrant ‘Q1’ represents parts of the field that may receive weed control measures due to the high disservice and low service potential, ‘Q3’ and ‘Q4’ could be left untreated based on a high or low service but low disservice potential. The ‘Q2’ shows a high conflict potential for weed management decisions based on a high potential for both service and disservice. When using thresholds of 50% for service and disservice potential around 60% of the field showed a high service and 34% a high disservice potential with about 32% of the field exhibited a combination of both. While this approach provides direct support for management decisions for ‘Q1’, ‘Q3’ and ‘Q4’ solving the balance between service and disservice potential, ‘Q2’ requires more complex management decisions. These may include additional, in-depths consideration of the specific weed species and their traits present at the ‘Q2’ locations and may be dependent on the farmers risk perception. As ‘Q2’ locations represent a higher disservice potential, negative impacts on crop productions might be expected.

The weighting of trait values and the adjustment of threshold offers additional flexibility to customise our approach to individual field conditions and specific weed management goals. In the present study, we weighted all traits equally not putting emphasis on specific traits. For fields where the goal is to increase the pollinator activity, the traits ‘pollinators’ and ‘flowering duration’ could be weighted higher. By adjusting the thresholds for service and/or disservice potential, management decisions can be customised to the individual field-specific conditions. While we set both the thresholds to 50%, the threshold for disservice potential could be lowered for fields where higher weed control level is required.

3.5.2. Weed Trait Data Availability

The service and disservice traits used in this study are commonly used to describe the competitive potential and ecological services provided by weed species (Bàrberi et al., 2018; Bosch et al., 2022; Pakeman et al., 2015; Storkey, 2006). We have focused on those traits for which comprehensive data for all weed species covered in this study was available from single field experiments, although additional traits could be relevant for describing the service (e.g., flower dimensions, odour and colour) and disservice (e.g., plant morphology, vegetative shoot and root characteristics) potential of a weed species (Gaba et al., 2017). Since trait values can vary greatly depending on the site-specific conditions, spatial distribution (like nests) of weeds, management practices and trait measurement method (Jørnsgard et al., 1996), we decided to use only data that were generated in the same experiment when describing individual traits.

We normalised weed functional trait values by comparing the five weed species present on our study field. Normalisation facilitates a comparison of the relative (dis-)service potential of the specific areas of the field, which can be very useful for the concrete consideration of on-field management decisions. In addition, this approach can also be used to compare the (dis-)service potential of the weeds in the study field with other winter wheat fields. This requires a trait survey and subsequent normalisation for all species relevant as weeds in winter wheat under typical German growing conditions. Gathering comprehensive trait data for such a high number of species is proving difficult due to fragmented and incomplete published trait information (Zingsheim and Döring, 2024). For future work, measurement of service and disservice traits under similar and comparable conditions is recommended even it is known to be challenging, especially for service traits.

3.5.3. Future Integration of (Dis-)Service Potential of Weeds SSWM

The two aggregated (dis-)service distribution maps can provide the basis for designing SSWM approaches that incorporate both beneficial and adverse weed functional traits. In this study, a grid with 40 points and distances of 6 m × 10 m between grid points was used for the manual weed assessment. Because of this coarse grid design, a potential patchiness of the actual weed occurrence might not be accurately represented in the interpolated weed distribution results. To capture the existing weed distribution on the field more accurately, an even finer grid design with lower distances between grid points would be beneficial to decrease potential inaccuracies resulting from interpolating weed count data in-between the grid points. Considering the time and expertise required to identify and count weeds at a high number of grid points, the detection and assessment of the spatial distribution of weeds needs to be further automated (Rai et al., 2023). This includes an automatic and reliable detection and identification of weeds on a species level as well as the use of image acquisition vehicle such as UAV, which could significantly simplify the process and thereby increase the practical uptake of site- and species-specific weed management (Veeranampalayam Sivakumar et al., 2020). Due to the high acquisition costs of the technologies (sprayers, cameras, etc.), the long-term benefits of the change in management must be made clear and the economical sustainability must also be discussed.

The approach presented here could be an integrated step between weed monitoring and weed management that allows weed management strategies to be site-specific and tailored to the individual weed species and their functional traits. The generated (dis-)service distribution maps illustrate the spatial correlation between service and disservice provision in the field based on the weed distribution. To our knowledge, no comparable approach exists that incorporates the spatial pattern of weed functional traits into field-specific maps for (dis-)service provision. The presented (dis-)service ratio field map can be used as a first step for a new version of weed management maps used for site-specific herbicide applications (e.g., using spot spraying approaches). As part of spot spraying, precise application of herbicides by single-nozzle control of the sprayer allows the field to be divided into small herbicide-treated and untreated patches. Adding the presented approach to this concept, herbicides are only applied on those parts of the field with a high competition ability and low biodiversity functions. The study presented an approach that could not only reduce the application of herbicides but also make a statement about the potential of the ecological service provided by weeds in an agricultural field. The results of this study in the form of maps can also be applied to overview and visualize the service and disservice potentials in a field, and even to monitor changes within a short or longer period.

3.6. Acknowledgements

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4. Trait-Based Weed Control Decisions Compared to Economic Thresholds for Site-Specific Weed Management

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4.1. Abstract

Four decision concepts were tested for ex-ante chemical weed control decisions for integration into site-specific weed management (SSWM). Two concepts assess the economic profitability of a weed control treatment: one considers the abundance of weed taxonomic groups, and the other takes into account individual weed species. The third and fourth concepts use weed functional traits to quantify species' ability to provide ecosystem services (service potential) and their competitive ability (disservice potential) in order to derive management decisions.

Based on grid-based manual weed assessments in five winter cereal fields in Germany, species-specific weed distribution maps were created using an interpolation approach. For each square meter of the fields, a weed control recommendation was generated using each of the four decision concepts, followed by the creation of weed control maps.

Control recommendations by the two economic decision concepts showed the highest similarity across all fields, recommending weed control for 23%–100% (weed groups) and 6%–100% (species-specific) of the total field area. The concepts based on functional weed traits recommended weed control for 2%–50% of the area.

Both economic decision concepts recommended a weed control treatment in areas recommended to be left untreated when functional traits are considered. The analysis revealed strengths and weaknesses in all concepts and recommends combining functional weed traits and economic profitability.

Keywords: Site-specific weed management, economic threshold, trait-based threshold, service, disservice, weed distribution maps

4.2. Introduction

The intensification of agricultural practices, such as increased herbicide use and simplified crop rotation, have contributed to the drastic decline in weed species diversity observed over the last decades (Hyvönen and Salonen, 2002; Potts et al., 2010). Arable weeds are often regarded as a leading cause of crop yield losses, even though a high weed species diversity in arable fields could offer ecological and economic advantages (Storkey and Neve, 2018). Increasing concern about the environmental impacts of herbicides and political efforts such as the European Green Deal have strengthened the development of more targeted and sustainable weed control concepts. An option to reduce herbicide use is site-specific weed management (SSWM), targeted at spatial areas of the field with specific weed abundance. By using boom section control, individual nozzle control, or spot spraying technologies, herbicides can be applied precisely on these defined parts of the field (Gerhards et al., 2022). Nordmeyer (2006) reported that herbicide treatments were required only for 39%–49% of the area in five cereal fields in Germany. Developing new digital technologies for precise weed management also offers great potential for SSWM. For example, in the future, it might be possible to automatically distinguish between individual weed species using artificial intelligence with image recognition algorithms (Hasan et al., 2021). Detecting weeds at the species level facilitates the integration of species-specific threshold concepts into SSWM, resulting in a more precise application of herbicides.

In an agricultural context, it is often assumed that weed control is generally economically profitable due to the yield loss induced by weed competition. However, multiple studies showed otherwise (Gerowitt et al., 1984; Koch et al., 1981; Niemann and Grigo, 1980). To help farmers make the pre-treatment (ex-ante) decision on whether a weed treatment control for a field will be economically profitable, fixed economic thresholds for mono- and dicotyledonous weeds were developed in the 1980s (i.e., Gerowitt and Heitefuss, 1990). If the threshold value for one of the two weed taxonomic groups is reached, the cost of the possible negative consequences caused by the weed infestation is assumed to exceed the costs of weed control treatments. Based on 25 winter wheat trials, Heitefuss et al. (1987) showed that ex-ante weed control decisions using fixed economic thresholds yielded a positive economic net return in approximately 80% of below-threshold cases (no treatment) and 52% of above-threshold cases (treatment applied). Therefore, a considerable percentage of weed control treatments could be omitted without a high economic risk. Fixed economic thresholds concepts commonly use a small number of manual spot-check weed assessments, which are then taken as representative for the entire arable field.

A study applying different varieties of economic thresholds based on taxonomic groups in SSWM indicated a potential herbicide saving of 36% in comparison to a whole-field blanket application for a herbicide mixture (Keller et al., 2014). In comparison to the SSWM, using a single field-wide recommendation results in a blanket weed control application based on the economic thresholds. A study by Hamouz et al. (2013) confirmed the saving potential of SSWM, showing that herbicide use could be reduced by 15–100% compared with blanket weed control, without any decrease in winter wheat yield.

The economic threshold concept further evolved to more complex economic thresholds based on species level, enhancing its practicality since the 1980s (Steinmann et al., 2021). These thresholds were developed in Germany in the late 1990s/ early 2000s to be used in decision support systems (DSS). Based on cost models, these DSS provide economically feasible ex-ante weed control decisions for individual weed species composition in a specific field (Bensch et al., in Print; Werner et al., 2004). In the past, studies implemented DSS into SSWM on the weed species level (Christensen et al., 2003; Lamastus-Stanford and Shaw, 2004). Integrating a DSS for weed control recommendations in soybeans, resulted in herbicide savings potentials varying from 0% to 49% (Lamastus-Stanford and Shaw, 2004).

While the economic threshold concepts focus on the economic benefits of weed control by using the cost of herbicide application and yield revenue as input variables, the ecological benefits provided by weeds (e.g., support of pollinators, natural enemies) or the environmental detriment side effects caused by herbicide use are not considered. The relevance of including ecosystem service provision by weeds into threshold concepts has been known for a long time (Franz, 1978; Steiner, 1968) and has received increasing scientific attention in recent years (Blaix et al., 2018; Esposito et al., 2023; Fanfarillo and Kasperski, 2021; Gerhards et al., 2022; Steinmann et al., 2021). If all costs, economic and ecological, are considered, a long-term sustainable weed control seems possible, while minimizing negative environmental impacts (DiTommaso et al., 2016). Schatke et al. (2024) have developed a site-specific recommendation based on species-specific functional traits allowing for the application of SSWM methods that effectively reduce weed species with strong competitive traits (disservice potential) and support weed species with strong beneficial traits (service potential) on a field.

In recent years, rapid advances in artificial intelligence have significantly improved the automatic identification of weed densities on the species level. Building on this, a subsequent step is required to determine ex-ante whether weed control is economically and ecologically beneficial in defined spatial areas of the field. To our knowledge, no comparison of different weed control recommendation concepts based on the economic and ecological potentials of the weed infestations and their potential use in SSWM exists. This work therefore addresses the difference in the herbicide treatment recommendation for SSWM between four concepts: site-specific economic thresholds based on taxonomic groups (SS_econ_grp), site-specific economic thresholds based on species-level (SS_econ_spcs), and two variations of site-specific recommendation based on species-specific functional traits. One of them addressing the reduction of economic risk (SS_traits_spcs (focus disservice)), and the other focusing on conserving the services provided by the weeds (SS_traits_spcs (focus service)) developed by Schatke et al. (2024). Using the different concepts as a decision tool for SSWM, we compare and discuss: (1) how weed control decisions based on the economic threshold concepts differ for SSWM in comparison to the current application (decisions for the entire field); (2) how weed control decisions for SSWM change when weed functional traits are incorporated into the decision-making process; (3) potential benefits and disadvantages of each threshold concept.

4.3. Methods

Five arable fields (field 1–5) in two different geographical locations in Germany (Location 1 and 2) with winter cereals were used for the comparison of the three threshold concepts: site-specific economic thresholds based on taxonomic groups (SS_econ_grp), site-specific economic thresholds based on species level (SS_econ_spcs), and two varieties of site-specific recommendation based on species-specific functional traits: one addressing the reduction of economic risk (SS_traits_spcs (focus disservice)), and the other focusing on conserving the services provided by the weeds (SS_traits_spcs (focus service)).

4.3.1. Data Sampling

Locations and fields

One field monitoring (field 1) was carried out in 2004 at Dikopshof Research Station (Location 1) near Cologne (Western Germany) in winter barley (*Hordeum vulgare* L.; Figure 4.1 (a)).

The soil was a silty loam, the average temperature 9.7°C (2003/2004), and 630 mm average precipitation (Gerhards and Oebel, 2006). Three study fields (fields 2–5) near Braunschweig ('Location 2'), Central Germany, were situated with a close distance to each other (1–4 km). The mean annual precipitation was 643 mm and the mean annual temperature was 9.4°C (2022/2023). A spatial grid for manual weed assessment (Table 4.1) was installed in the center of each of the three winter wheat (*Triticum aestivum* L.) fields (Figure 4.1 (b)).

Location 1 was in less proximity to the Location 2 (400 km distance) and was selected to ensure that the location-specific conditions differed. At all five fields, fertilizer, plant growth regulator, fungicide, and insecticide applications were conducted according to common agricultural practices. At each field, no herbicide treatment was carried before the weed assessment.

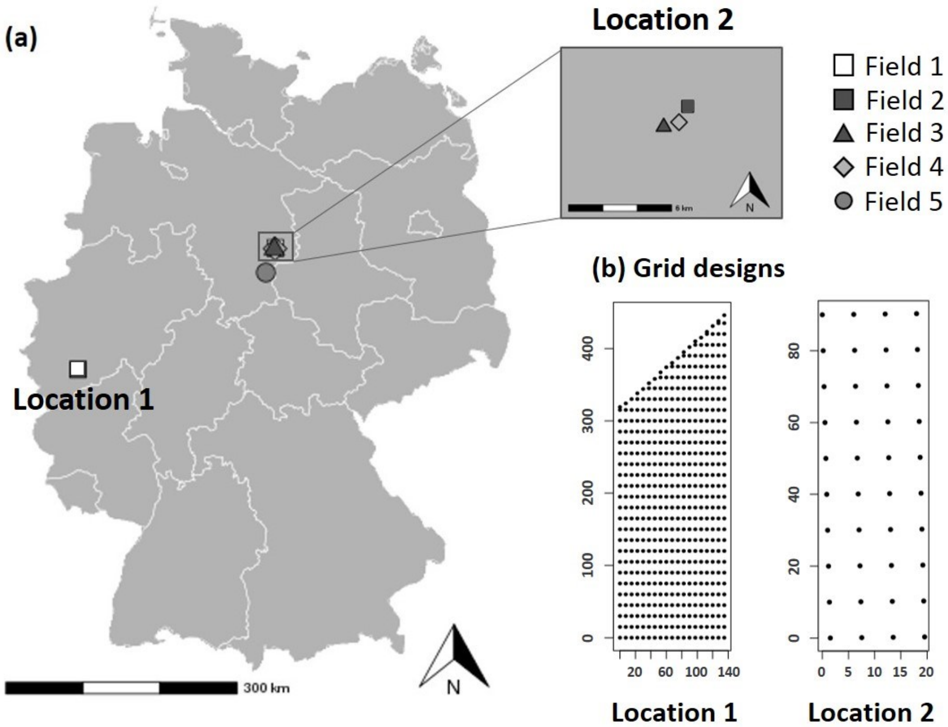

Figure 4.1: (a) Map of Germany with fields 1–5. (b) Grid designs (distance in m) for the weed assessments at Location 1 (field 1) and Location 2 (fields 2–5). The grid in Location 1 is depicted with a different spatial scale than Location 2.

Table 4.1: Description of the experimental fields at Location 1 (field 1) and Location 2 (field 2–5).

	Location 1	**Location 1**			
	Field 1	**Field 2**	**Field 3**	**Field 4**	**Field 5**
Crop type	Winter barley (*Hordeum vulgare* L.)	Winter wheat (*Triticum aestivum* L.)	Winter wheat (*Triticum aestivum* L.)	Winter wheat (*Triticum aestivum* L.)	Winter wheat (*Triticum aestivum* L.)
Location	50°48'28.9"N 6°57'10.6"E	52°13'28.9"N 10°37'49.2"E	52°12'50.3"N 10°36'38.7"E	52°12'59.7"N 10°37'29.0"E	51°56'17.9"N 10°27'13.5"E
No. grid points	510	40	40	40	40
Grid distance	7.5m × 15 m	6m × 10m	6m × 10m	6m × 10m	6m × 10m
Total area	319m × 446m (0.006 ha)	24m × 100m (0.0024 ha)	24m × 100m (0.0024 ha)	24m × 100m (0.0024 ha)	24m × 100m (0.0024 ha)

Assessment of the Weed Vegetation for Distribution Maps

Weed sampling was performed in spring at each grid point after sowing of the crop plant and before the first herbicide was applied by counting the number of weed plants per species using a metal counting frame with a size of 0.1 m^2.

To generate species-specific weed distribution maps for each field based on these data, an Inverse Distance Weighting (IDW) interpolation was applied to estimate weed densities in the areas between the grid points (Schatke et al., 2025). The interpolated distribution maps had a resolution of 0.1 m × 0.1 m, which was aggregated to a pixel resolution of 1 m × 1 m. This spatial resolution was chosen because the fixed economic threshold concept is based on measuring plants per square meter, and the resolution aligns with the available tools for SSWM.

4.3.2. Weed Control Recommendations

Site-specific weed control maps were calculated for each field and the four threshold concepts (Figure 4.2). Based on these maps, each field is divided into spatial areas where either a weed control treatment is recommended (treatment recommended) or no control is required (no treatment recommended). In an additional step, field-wide recommendation were calculated to represent the current way of application of economic thresholds (single field-wide recommendation). The treatment recommendations solely considering weed control with herbicides (SS_econ_grp and SS_econ_spcs) were developed based on costs related to herbicide application.

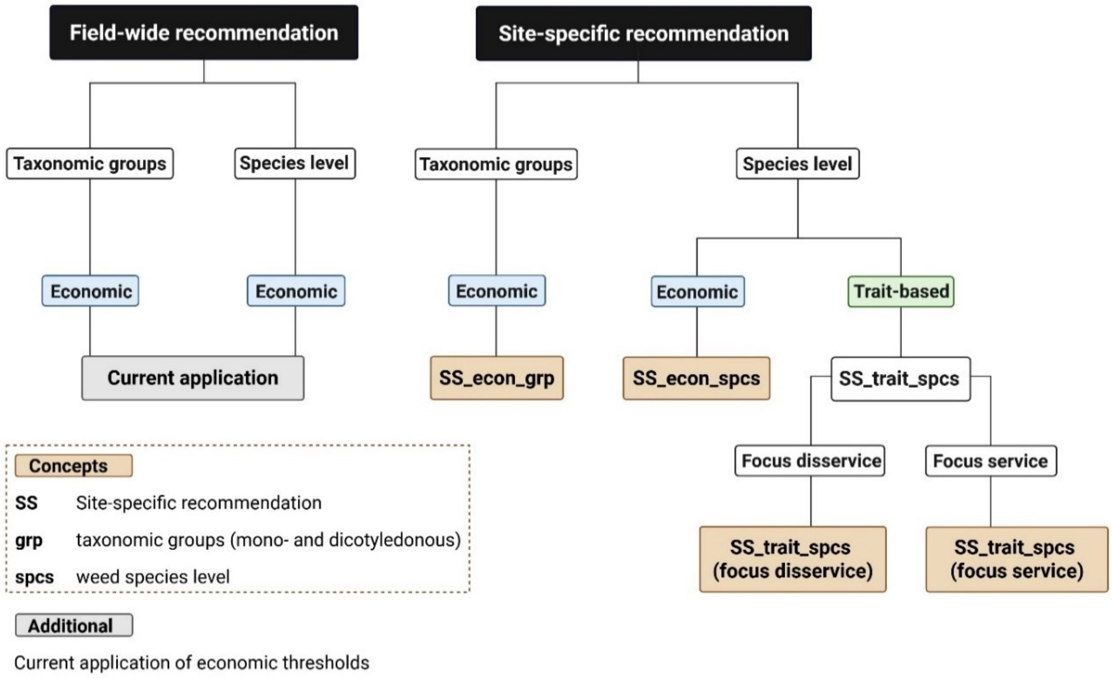

Figure 4.2: Weed control recommendation concepts (orange) for SSWM used in this study. Recommendations were made based on weed taxonomic groups or at the species level, and by economic thresholds or functional traits. Recommendation on field-wide level represents the current way of application of economic threshold concepts (single field-wide decision).

Site-Specific Economic Thresholds based on Taxonomic Groups (SS_econ_grp)

Fixed economic thresholds estimate a specific density at which the costs of weed control are lower than the estimated economic loss by yield reduction. As this concept was developed in the 1980s and the numbers were never updated, the thresholds are still based on herbicide costs and market prices from the 1980s. The observed weeds were divided into two taxonomical groups with fixed economic thresholds: monocotyledonous with a threshold of 20–30 plants m^{-2} and dicotyledonous weed species with a threshold of 40–50 plants m^{-2} (Gerowitt and Heitefuss, 1990). Exceptions apply to the weed species *Galium aparine* L. with threshold of 0.1–0.5 plants m^{-2} and *Fallopia convolvulus* (L.) Löve with a threshold of 2 plants m^{-2}. A common problem associated with the interpolation of the weed distribution is the smoothing effect, resulting in predictions of lower maximum and higher minimum densities for the study fields when compared to the actual measured densities (Schatke et al., 2025). Even though the chosen interpolation method (IDW) usually results in a lower smoothing effect compared to other interpolation methods like Kriging, we decided to choose the lowest thresholds values out of the range of fixed economic thresholds to generate weed control recommendations for the two groups mono- and dicotyledonous weed. As an exception, the highest value (0.5 m^{-2}) of the threshold span of the economic thresholds was selected for *G. aparine* as very low density values are often overpredicted when interpolated due to the smoothing effect. This effect makes it difficult to accurately predict values below plant densities of 0.5 plants m^{-2}, even in areas where no individuals of the weed species were observed. For mono- and dicotyledonous weeds, the numbers of all plants of the group are summed up for each pixel point and then compared with the threshold values. The densities (plants m^{-2}) in each pixel of the weed distribution maps were compared to the economic thresholds based on taxonomic groups to decide about their control recommendation. If the density of a weed group exceeds the threshold value for a given pixel of the weed distribution map, the pixel area is recommended to be treated.

Site-Specific Economic Thresholds Based on Species Level (SS_econ_spcs)

Like the economic thresholds based on taxonomic groups, SS_econ_spcs relates weed control decisions to the economic profitability of the weed control treatment (Werner et al., 2004). For this, economic profitability for each pixel of the weed distribution map (1 m^2) relates the yield loss caused by the weed infestation and the costs of control to generate weed control recommendations. The treatment is considered profitable if the expected yield loss (Eq. 4.1) exceeds the cost of the control value at pixel *i*. While the costs of weed control are the same for the entire field, the estimated yield loss varies with the presence of different weed species at each pixel, resulting in different weed treatment recommendations.

To calculate the yield loss caused by the weed infestation at each pixel (*i*) of the weed distribution maps in proportion to weed-free yield ($yield\ loss_i$), the following equation was used:

$$yield\ loss_i = \sum \frac{YLP_{species} \times density_{species} \times max\ (density_{total})}{YLP_{max} \times density_{total} + max\ (density_{total})} \tag{4.1}$$

The yield loss parameter ($YLP_{species}$) is species- and crop-specific and represents the yield loss caused by a single weed plant per species in relation to the potential yield in a weed free field (Werner et al. 2004). The maximum yield loss parameter YLP_{max} describes the maximum possible yield loss caused by weeds. The $density_{total}$ (plants m^{-2}) describes the actual total density at each pixel i. The maximum possible density of all weed plants $\max\ (\mathrm{density}_{total})$

depends on the season and the development stage of the crop and can range from 3000–5000 weed plants m^{-2} and is based on expert knowledge (Bensch et al., in Print).

The costs of control (C_{cost}) are calculated by dividing the costs of control by the expected weed free total market value (C_{max}), calculated by multiplying the potential yield in the weed-free crop ($Y_{weedfree}$) with the market value per crop production unit (V; Eq. 4.2):

$$C_{cost} = \frac{C_{max}}{Y_{weedfree} \times V} \tag{4.2}$$

The yield loss caused by the weed infestation in proportion to weed free yield was calculated for each pixel of the weed distribution maps (Eq. 4.1). The maximum possible YLP_{max} due to weeds were estimated by experts to be 50% (Bensch et al., in Print). Thus, YLP_{max} is 0.5. The $\max\ (\text{density}_{total})$ was set to 4000 weed plants m^{-2} based on the season (spring) and the development stage of the winter cereals (BBCH 12-29; (Bensch et al., in Print)).

The costs of chemical weed control in winter wheat (C_{cost}), including the herbicide product price and application costs, are based on contribution margin data provided by LfL Bavaria (LfL: Bayerische Landesanstalt für Landwirtschaft, 2025), which reflect federal state averages from 2021 to 2023. The herbicide product cost is €57.76 ha^{-1}, with an additional application cost of €12.17 ha^{-1}, resulting in a total control cost (C_{cost}) of €69.93 ha^{-1}. Based on statistical data from previous years (Germany, 2022–2023), we derived the mean market value of winter wheat as 0.30 € kg^{-1} (V) (Statistika, 2024b) and the mean weed free yield expectation as 7540 kg ha^{-1} ($Y_{weedfree}$) for Germany (Statistika, 2024b). The same approach was applied to winter barley. The product price is 59.79 € ha^{-1}, with an additional application cost of 10.02 € ha^{-1}, resulting in a total control cost (C_{max}) of 69.81 € ha^{-1} (LfL: Bayerische Landesanstalt für Landwirtschaft, 2025). The mean market value (V) of 0.19 € kg^{-1} (Statistika, 2024a) and the mean weed-free yield expectation ($Y_{weedfree}$) of 7430 kg ha^{-1} are based on statistical data from Germany (2022–2023). By inserting these values into equation 4.2, the threshold value for the costs of control is 0.031 for winter wheat and 0.049 for winter barley.

Site-Specific Recommendation Based on Species-Specific Functional Traits

Functional trait values for each weed species relevant for winter wheat and winter barley were collected from published literature and online sources. Traits describing the beneficial ecological services provided by the weed species (service potential) were selected as well as traits related to the competitive potential of weeds or their negative impacts on crop production (disservice potential). The threshold concept is further explained in the study of Schatke et al. (2024). The service potential of a weed species was described by the number of links between this species and natural enemies of arthropods, phytophagous arthropods, pollinators, birds directly feeding on the weed (seeds) and birds of prey that feed on birds directly associated with the individual weed (Bosch et al., 2022). Other service trait were the duration of flowering in months and the number of links with insect families, insect species, and host specific insects by Marshall et al. (2003).

Four traits represented the weeds' competitive ability: the yield loss parameter as used in SS_econ_spcs, representing the yield loss caused by a single weed plant per species in relation to the potential yield in a weed-free field. The 'specific leaf area' represents the ratio between plants' leaf area of the fresh leaf and leaf dry mass (SLA; $cm^2\ g^{-1}$) collected by Bàrberi et al. (2018). The vegetative trait 'plant height vegetative' is the distance between the uppermost tip of the photosynthetic tissue of the weed plant and the ground level in meters (Pakeman et al., 2015). 'Pest species' represents the number of observed links between the weed species and pest arthropods (Bosch et al., 2022).

Schatke et al. (2024) normalised service and disservice traits to values between 0 and 1 among all species which they observed on their study fields. Deviating from this approach, the service and disservice trait values were collected for the weed species most likely be observed in winter cereals in Germany (expert knowledge; Table S7 – supplemental material). These trait values were normalized from 0 to 1 better to compare the five fields (Table 4.2).

$$WT_i = \frac{\sum(N_{S_i} \times T_S)}{\sum No.Weeds_{S_i}} \tag{4.3}$$

The weighted trait (WT) for each pixel i of the weed distribution map was determined for all services and disservices separately (Eq. 4.3). The variable i refers to a specific pixel of the weed distribution maps. S represents a particular weed species, N_{S_i} is the weed density of species S found at pixel i (individual plants per m^2), and T stands for the trait value of species S. The variable $No.Weeds_{S_i}$ represents the sum of individual plants of all weed species occurred at the pixel i. The result is a new trait distribution map for each weighted trait. A high (dis-)service potential exists at a value of 1, an average one at 0 and a low one at -1.

To further condense the service and disservice trait distribution maps, a principal component analysis (PCA) was used (Schatke et al., 2024). The PCA was conducted using a) the pixel information of the service trait distribution maps, and b) of the disservice trait potential maps. The outcomes were two spatial field maps, the disservice potential distribution map and the service distribution map. Afterwards, a correlation analysis and scatterplot analyze the ratio between disservice and service potentials (Figure 4.5 (a)). To create the final management recommendations, the scatter plot is divided into four quadrants based on hypothetical thresholds (service and disservice potential = 0):

- Pixels with high disservice, low service potential (Q1)
- Pixels with high disservice, high service potential (Q2)
- Pixels with low disservice, low service potential (Q3)
- Pixels with low disservice, high service potential (Q4)

For Q1, weed control is recommended, as the disservice potential is higher than the service potential. For Q3 and Q4 (disservice potential is low), no control is recommended. For Q2, the decision is complex, as both the service and the disservice potentials are high. We therefore compare two different variations of weed control recommendations for Q2 based on functional traits in this study:

1. SS_traits_spcs (focus disservice): the area with high disservice potential is recommended to be treated regardless of the high service potential.
2. SS_traits_spcs (focus service): the area with high service potential is recommended not to be treated regardless of the high disservice potential.

Comparing Current Application of Economic Threshold Concepts with SSWM Application (Additional)

The SS_econ_grp and SS_econ_spcs concepts are not intended to be used in combination with SSWM. Currently, the weed density is randomly spot-checked on a limited number of sampling points in the field, and it is then determined whether the average weed density exceeds the respective threshold value. If this is the case, a blanket weed control treatment is recommended for the entire field. In this study, the current application of economic threshold was tested by calculating the mean densities of all grid points for each weed taxonomic group (as in SS_econ_grp) or species (as in SS_econ_spcs) as an alternative to the current spotchecking. Relating these to the threshold values delivered a single weed control recommendation for the entire area (blanket application recommended or no treatment recommended). This single weed control recommendation was compared to the weed control recommendation using economic thresholds in combination with SSWM.

4.3.3. Analysis: Comparing Output Maps

The simple matching coefficient compares the values of each pixel in the output maps for similarities in the weed control recommendations (treatment recommended or no treatment recommended) between the four weed control concepts. The coefficient was calculated by dividing the number of pixels with matching recommendations by the total number of pixels. The value ranges from 0 to 1; the higher the value, the greater the similarity.

4.4. Results

The results of each calculation step from the weed assessment in the field to the weed control maps are illustrated using the data from field 1 (Location 1) and field 4 (Location 2). For fields 2, 3, and 5 only the final weed control recommendations (areas recommended to be treated) are presented and discussed, and the additional data are listed in supplemental material (6.3.1 Chapter 4).

4.4.1. Field 1 (Location 1)

Weed Distribution Maps

The number of weeds observed at each grid point was interpolated over the entire field to create a weed distribution map for each species observed (Figure 4.3). For field 1, the species with the highest mean density was *Alopecurus myosuroides* Huds. (9 plants m^{-2}), with high densities at the upper and lower left parts of the field. The second highest mean density had the species *Veronica hederifolia* L. with 4 plants m^{-2} and a high density on the left edge of the field. In addition, *A. myosuroides* was observed with the highest maximum density per pixel with 266 plants m^{-2} and *V. hederifolia* with the second highest maximum density (190 plants m^{-2}). *G. aparine* was observed with a maximum density of 33 plants m^{-2}. The species *C. arvense* and *G. dissectum* occurred with a maximum of less than 5 plants per m^{-2}.

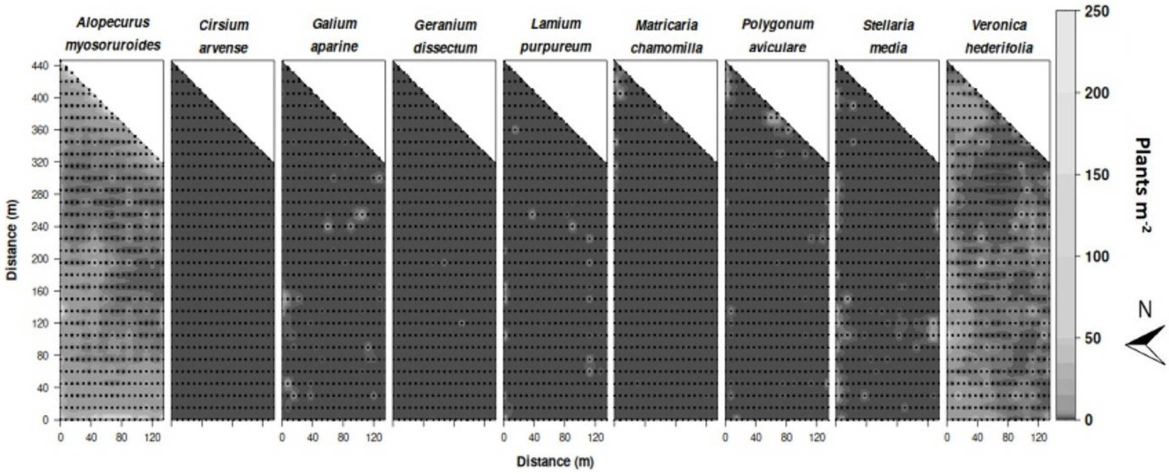

Figure 4.3: Weed distribution maps for the species observed on field 1. The black dots represent the sampling grid points.

Site-Specific Economic Thresholds Based on Taxonomic Groups (SS_econ_grp)

The threshold of 40 plants m^{-2} for dicotyledonous plants was exceeded at the left edge for 0.3% of the field. A weed control based on SS_econ_grp is recommended for the field edges, where *A. myosuroides* exceeded the threshold of 20 plants m^{-2} (Figure 4.4). *G. aparine* also exceeded the control threshold of 0.5 plants m^{-2} at each grid point where it was observed, resulting in treatment recommendations for some clusters in the field center. In an SSWM concept, about 77% of the field can be left untreated based on the SS_econ_grp concept.

Site-Specific Economic Thresholds Based on Species Level (SS_econ_spcs)

The species *G. aparine* has the greatest yield loss parameter (YLP; 0.015) and thus, caused the greatest estimated relative yield loss. The YLP of *G. aparine* is almost ten times as high as for the species *A. myosuroides* (0.0011), *C. arvense* (0.0015), and *Lamium purpureum* (0.0011). The second greatest YLP is connected to the species *S. media* (0.0024). The species with the lowest estimated YLP are *V. hederifolia* and *P. aviculare* (both 0.00018). If a weed control decision was made for a SSWM, weed control was recommended for only 6% of the area (Figure 4.4).

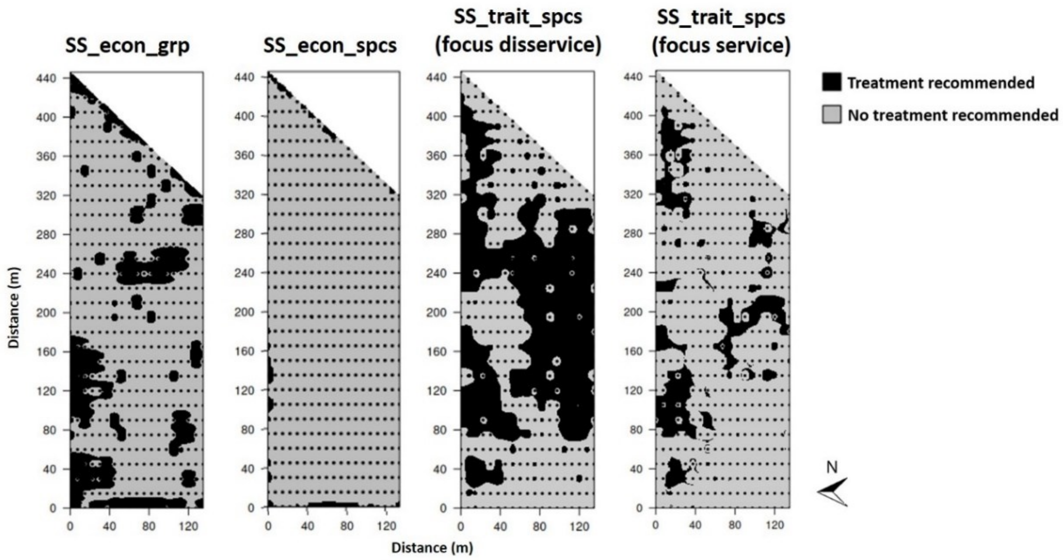

Figure 4.4: Weed control maps based on the different concepts for field 1. For the black areas, a weed treatment is recommended whereas no treatment is recommended for the light grey areas. Black dots represent the sampling grid points.

Site-Specific Recommendation Based on Species-Specific Functional Traits

The species observed in fields 1–5 are listed, along with their normalized trait values, in Table 4.2. The species *C. arvense* has the highest mean value (0.69) for the service traits compared to the other weed species. For the traits 'insect species' and 'birds direct', *C. arvense* is not the species with the highest links, instead, it is *S. media*. Overall, *S. media* has the second-highest mean value for service traits (0.61). *V. hederifolia*, *G. dissectum*, and *Lamium sp*. show the highest 'competitive index' as a disservice trait. The highest value for 'SLA' is assigned to *S. media*, the highest links to 'pest species', and the highest 'plant height' to *C. arvense*.

Table 4.2: Service and disservice trait values for each weed species observed in the five experimental fields. The values are normalized to values with a range of 0–1. Further trait data for weed species relevant for winter cereals, used for the normalization process, can be found in the supplements (Tab. S1).

Species	**Relative yield loss (wheat)**	**Relative yield loss (barley)**	**Pest species**	**Specific Leaf Area**	**Vegetative Plant Height**	**Natural enemies**	**Phytophages**	**Pollinator**	**Birds direct**	**Birds indirect**	**Insect families**	**Insect species**	**Host-specific insects**	**Flowering duration**
A. myosuroides	0.07	0.07	0.75	0.39	0.17	0.21	0.27	0.03	0.00	0.00	0.06	0.07	0.00	0.28
C. arvense	0.10	0.11	0.44	0.12	0.79	1.00	1.00	1.00	0.38	0.33	1.00	0.70	0.71	0.11
G. aparine	1.00	1.00	0.03	0.56	1.00	0.00	0.93	0.18	0.38	0.00	0.67	0.41	0.57	0.23
G. dissectum	0.05	0.05	0.09	0.29	0.31	0.00	0.14	0.02	0.24	0.83	0.06	0.01	0.00	0.17
L. purpureum	0.07	0.07	0.09	0.65	0.21	0.00	0.44	0.21	0.24	0.83	0.39	0.24	0.29	0.40
M. chamomilla	0.05	0.05	0.31	0.29	0.10	0.14	0.26	0.12	0.05	0.00	0.44	0.20	0.14	0.17
M. arvensis	0.07	0.07	0.00	0.43	0.19	0.29	0.12	0.07	0.33	0.00	0.11	0.03	0.00	0.28
P. rhoeas	0.05	0.05	0.13	0.52	0.38	0.07	0.05	0.04	0.00	0.00	0.33	0.10	0.00	0.11
P. annua	0.01	0.01	1.00	0.59	0.00	0.21	0.95	0.15	0.29	0.33	0.78	0.74	1.00	0.63
P. aviculare	0.01	0.01	0.28	0.42	0.76	0.14	0.87	0.22	0.43	1.00	0.11	0.03	0.00	0.34
S. media	0.16	0.16	0.16	1.00	0.17	0.50	0.70	0.14	1.00	0.33	0.61	1.00	0.57	0.63
V. hederifolia	0.01	0.01	0.28	0.42	0.10	0.21	0.17	0.02	0.00	0.00	0.00	0.00	0.00	0.11
V. arvensis	0.07	0.07	0.13	0.32	0.12	0.14	0.28	0.07	0.62	0.00	0.06	0.01	0.00	0.34

After using a PCA, two new maps were created showing the service and disservice potential for each pixel in the field of field 1 (Figure 4.5). Both the service and disservice potential showed a similar distribution, with the highest values on the right side and in the center of the field. The lowest value for the service potential was -0.3, and the highest service potential was 1.39. The disservice potential ranged from -0.3 to 0.9, with a mean value of 0.

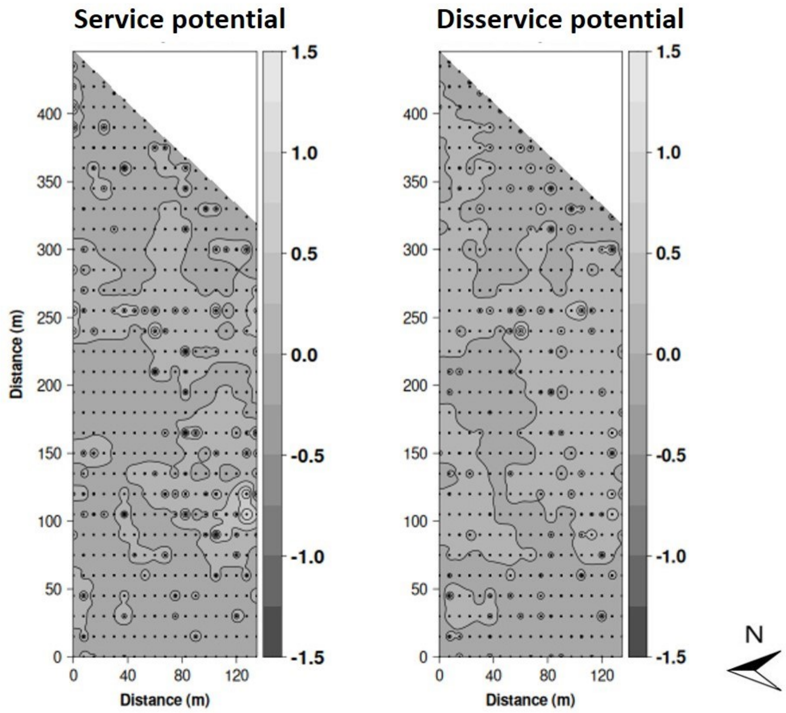

Figure 4.5: Service and disservice distribution maps with values from -1.5 (0% potential) to 1.5 (100% potential) in the field 1 showing the scores of the first axis of a PCA based on the occurrence of the weed species and the species-specific traits. Black dots represent the sampling grid points.

The control map, colored based on the scatterplot, shows that the area in the field with high service and disservice potential (Q2) was mainly in the center and right side of the field (Figure 4.6 (b)). Overall, the Q2-area is 17 544 m^2, which is 34% of the total field (51 600 m^2). In about half of the field (51%) the disservice potential was high (26 316 m^2). About 40% of the field shows a high service potential. The area of the field with a high service potential and low disservice potential is the smallest (6%; 3 096 m^2). SS_trait_spcs (focus service) recommended a weed control treatment for 17% of the field (Figure 4.4). SS_trait_spcs (focus disservice) resulted in a treatment recommendation for 41% of the field.

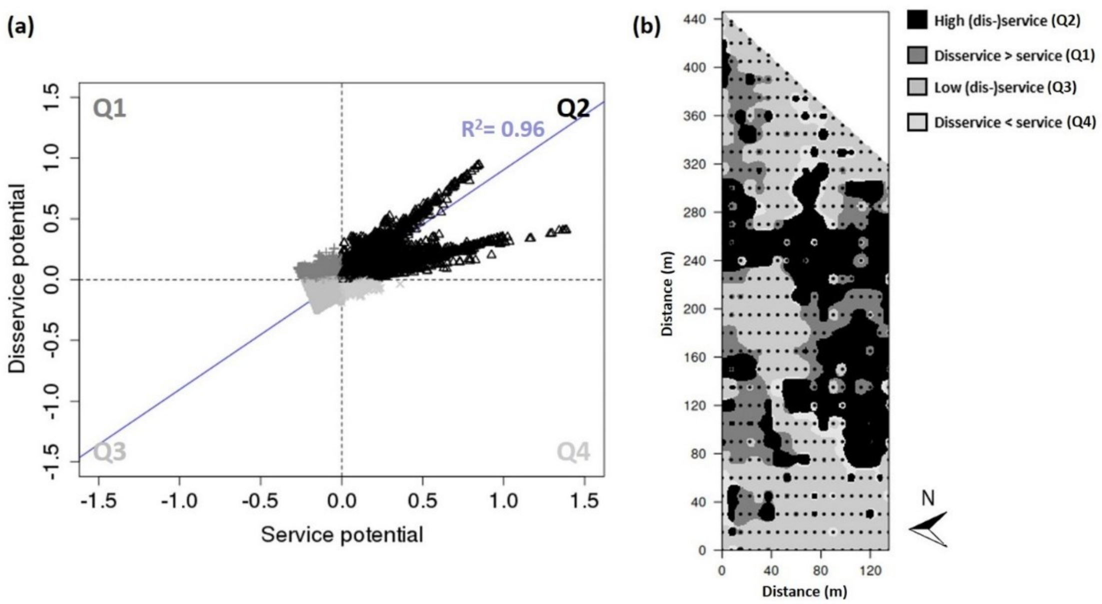

Figure 4.6: Correlation (a) between the pixel values of the service and the disservice distribution maps (Figure 4.5) with values from -1.5 (0% potential) to 1.5 (100% potential) and the Spearman Correlation Coefficient (blue). (b) The (dis-)service ratio field map was created based on the locations of the pixels in the four quadrants (a) using the same colors. Black dots represent the sampling grid points.

4.4.2. Field 4 (Location 2)

Comparable to field 1, the species *V. arvensis* occurred with the highest mean density (52 plants m^{-2}) on field 4 (Figure 4.7). The species with the second highest density was *A. myosuroides* with a mean of 29 plants m^{-2}. Two species had a mean density of 9 plants m^{-2}: *Papaver rhoeas* and *P. aviculare*. The maximum density values for *P. rhoeas* were mainly found in the top and bottom parts of the field and in the center and bottom parts for *P. aviculare*.

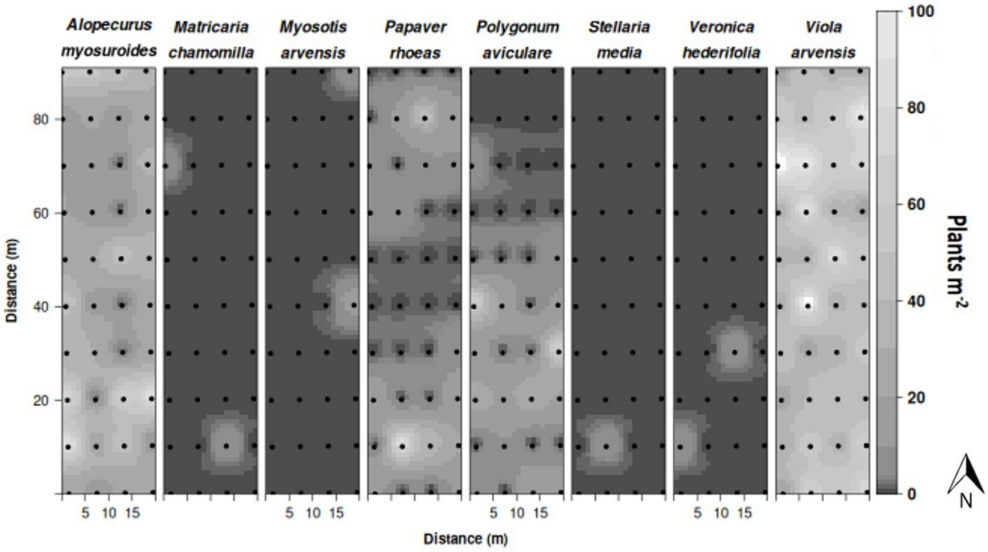

Figure 4.7: Weed distribution maps for the species observed in the experimental field at field 4. Black dots represent the sampling grid points.

The field area with a high service and low disservice potential was the largest (white area in Figure 4.8 (a); 40%), and the field area with low service and low disservice potential was the smallest (light grey area; 10%). The area with both high service and high disservice potential amounted to 20% (black area). The Spearman correlation coefficient between the service and disservice potential was –0.64.

Based on the concepts SS_econ_grp and SS_econ_spcs, recommendations to control for the entire field at field 4 were generated (Figure 4.8 (b)). For the concept SS_trait_spcs (focus disservice), 50% of the area was recommended to be left untreated, compared to 69% for SS_trait_spcs (focus service).

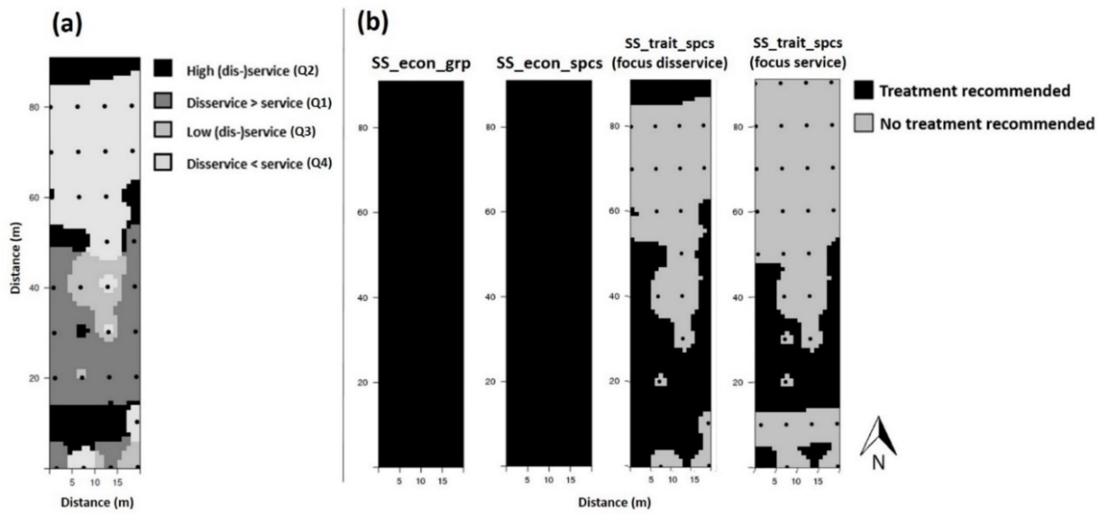

Figure 4.8: (a) Relation between service and disservice potential based on the SS_trait_spcs concept calculations. (b) Weed control recommendations based on different concepts for the field 4. Black-colored areas are recommended to be treated, and grey areas are not.

4.4.3. Comparing Current Application of Economic Threshold Concepts with SSWM Application (Additional)

The two economic threshold concepts, SS_econ_grp and SS_econ_spcs, were initially developed to generate a single field-wide weed control recommendation (blanket application recommended or no treatment recommended) without regarding spatial weed distribution in the field (Figure 4.2; additional). If field-specific mean weed density were considered, weed control would not be recommended for field 1 when using economic thresholds based on taxonomic groups (as in SS_econ_grp) and based on species-level (as in SS_econ_spcs). For all fields at Location 2 (fields 2–5), it would have been recommended that the fields be treated based on both economic threshold concepts.

4.4.4. Comparison of Treatment Recommendations

Both economic threshold concepts (SS_econ_grp and SS_econ_spcs) recommended weed control for larger areas of all fields, except for field 1, than the trait-based concept SS_trait_spcs (Figure 4.9). In contrast, for field 1, the area recommended to be treated was higher based on SS_trait_spcs (focus disservice) than for the two economic thresholds concepts. For fields 3–5, recommendations for weed control were provided for the entire field areas based on the two economic threshold concepts. The area recommended for weed control was smaller when using the SS_trait_spcs (focus service) compared to SS_trait_spcs (focus disservice) for all fields. Overall, all weed control decision concepts for fields 1 and 2 recommended that more than 30% of the area be left untreated.

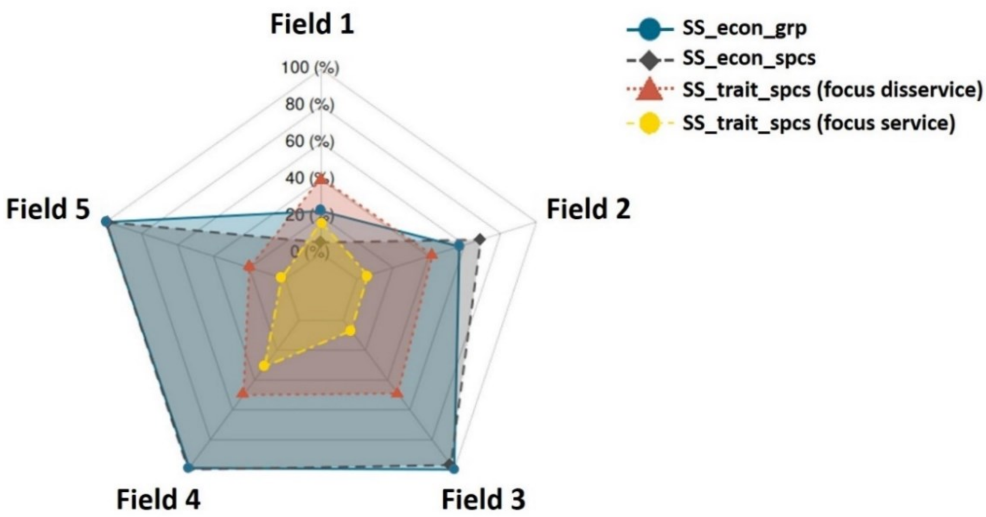

Figure 4.9: Percentage of field area with a recommendation for weed control for the five fields based on the four concepts SS_econ_grp, SS_econ_spcs, SS_trait_spcs (focus disservice), and SS_trait_spcs (focus service).

The similarities between the areas with the same weed control recommendation (pixel values based on the weed control maps) across the different concepts were expressed using the simple matching coefficients (Table 4.3). Across all fields, SS_econ_grp and SS_econ_spcs consistently resulted in similar or identical control recommendations. The simple matching coefficient between the two variations of SS_trait_spcs was higher than 0.5 for all fields. The lowest similarities were observed between the recommendation of SS_trait_spcs (focus service) and the two economic threshold concepts (SS_econ_grp and SS_econ_spcs) at fields 3 and 5.

Table 4.3: Simple matching coefficient between the weed management maps created by the four concepts.

Concept 1	Concept 2	Simple matching coefficient				
		Field 1	**Field 2**	**Field 3**	**Field 4**	**Field 5**
SS_trait_spcs (focus disservice)	SS_trait_spcs (focus service)	0.66	0.58	0.57	0.81	0.77
SS_trait_spcs (focus disservice)	SS_econ_grp	0.56	0.37	0.51	0.51	0.25
SS_trait_spcs (focus disservice)	SS_econ_spcs	0.46	0.61	0.49	0.51	0.25
SS_trait_spcs (focus service)	SS_econ_grp	0.67	0.47	0.07	0.32	0.02
SS_trait_spcs (focus service)	SS_econ_spcs	0.79	0.37	0.08	0.32	0.02
SS_econ_grp	SS_econ_spcs	0.81	0.77	0.97	1.00	1.00

4.5. Discussion

This study highlights the differences between current economic thresholds and novel trait-based concepts developed to support *ex-ante* decision processes for chemical weed control on arable fields and assesses their applicability for site-specific weed management (SSWM). While most economic threshold concepts, like the employed site-specific economic thresholds based on taxonomic groups (SS_econ_grp) and based on species-level (SS_econ_spcs), focus on the economic viability of a weed control treatment (potential financial loss due to yield reduction in relation to the weed control costs), we also employed the novel concept for site-specific recommendation based on species-specific functional traits (SS_trait_spcs) incorporating the ecosystem services of the weeds and weeds' adverse effects. Key findings from the comparison of weed control decisions based on the threshold concepts are highlighted in Chapter 4.5.1, and advantages and limitations of each concept are discussed within Subchapters in 4.5.2.

4.5.1. Field-Specific Results

The treatment recommendations provided by the three concepts varied depending on the field and the weed infestation level. The high similarity in the results between the economic threshold concepts can be explained by the fact that they both utilize the same input factors for the calculation of the threshold values: weed control costs, yield loss potential of the weed species or weed group, and the market value of the crop product. Even though the SS_econ_spcs uses species-specific threshold values, while the SS_econ_grp employs fixed threshold values for the two weed taxonomic groups, the results showed similar weed control maps for all fields.

The weed control maps for field 1 showed, on average, the highest simple matching coefficient, indicating similarities in the distribution of the area to be treated among all weed control concepts. In particular, the areas with the highest densities of *V. hederifolia* were mainly recommended to be treated by all concepts. For the concept SS_trait_spcs, this can be linked to the lower service than disservice potential of this species. The areas with high *A. myosuroides* densities (only the case for fields 3 and 4) were recommended to be treated based on the two economic threshold concepts, but not always based on the trait-based concept SS_trait_spcs. The species *A. myosuroides* is a very competitive grass weed, which has the potential to produce a large number of seeds, grows rapidly, and can cause considerable yield loss of up to 50% (Gerhards et al., 2016; Maréchal et al., 2012; Moss, 2017; Vizantinopoulos and Katranis, 1998; Zeller et al., 2018; Zeller et al., 2021). The species-specific viability of seeds in the soil is an important plant trait that has not yet been considered in the employed trait-based concept (SS_trait_spcs). In the future, additional plant traits, such as seed viability, which have high ecological and agronomic importance, should therefore be integrated into the trait-based concept.

The weed infestation on field 4 was high due to high densities of *V. arvensis*. In this case, the recommendations of the four concepts differed more pronouncedly. The species *V. arvensis* showed a high number of links to direct feeding birds and a longer flowering period than other relevant weed species in winter wheat. For the SS_trait_spcs concept, this has led to the decision not to recommend treatment in spatial areas of the field with high densities of *V. arvensis*. For the two economic threshold concepts, *V. arvensis* densities reached the economic thresholds over the entire field in field 4, and therefore, a weed control treatment was recommended. For fields 1, 2, 3, and 5, a similar distribution of service and disservice potential due to the field-specific weed composition was observed. This confirms the results of Yvoz et al. (2022), showing a positive correlation between the service and disservice provided by weeds, which is mainly affected by the abundance of the weed plants.

In the case of a weed species with higher values for traits describing disservice potential than service potential, such as *G. aparine,* a weed treatment is recommended based on all concepts except for SS_trait_spcs (focus service). Different from SS_trait_spcs (focus disservice), the area with high service potential is recommended not to be treated regardless of the high disservice potential. Therefore, the concept SS_trait_spcs (focus service) can tolerate weed species such as *G. aparine,* which has high disservice potential to preserve the service potential. This approach could be followed if the farmer prioritizes the ecological service potential of the present weed over the weeds' disservice potential.

The Figure 4.8 (a) shows field areas in field 4, where only the service potential was high. These areas would be recommended to be treated based on the two economic threshold concepts (Figure 4.8 (b)) and are recommended to be left out in the two variants of SS_trait_spcs. This result shows the potential to preserve important ecosystem functions of weeds by including functional weed traits in weed control decisions.

4.5.2. Opportunities and Limitations of the Concepts

Economic Thresholds

The concept SS_econ_grp was developed as one of the first weed control decision assistances before the common use of computer programs and served as a rather easily accessible information for farmers. Due to the lack of data for species-specific decisions, weeds are categorized into groups of mono- and dicotyledonous weeds. This simplification makes the concept user-friendly for manual weed assessments. However, the yield loss parameter of single weed species can differ substantially within the two taxonomical groups. For example, the yield loss parameter of *S. media,* implemented in the calculation of the SS_econ_spcs concept, was considerably higher than for the species *V. hederifolia,* but both species contribute to the group 'dicotyledonous weeds' of SS_econ_grp. However, our study indicates that, by incorporating the species-specific yield loss parameter, the concept SS_econ_spcs did not result in substantial differences in the generated weed control recommendations when compared to the SS_econ_grp concept, in which only the two weed groups are considered. Therefore, in this case, it would be sufficient to stay with SS_econ_grp.

The two economic threshold concepts were developed and employed before the advent of SSWM approaches. When we applied the economic threshold concepts to the mean density values for the entire field without regarding the spatial distribution, weed control treatments were recommended for all fields, except for field 1 at a different site in Germany (Location 1). In field 1, combining the economic threshold concepts with the SSWM approach resulted in a higher area that was recommended to be treated compared to the current application of the threshold concepts (for field 1: no weed control recommended). Unlike the observations of

Nordmeyer et al. (2003) and Keller et al. (2014), who reported greater herbicide savings with SSWM incorporating economic thresholds compared to current application, the results from field 1 did not reflect such advantages. The opposite was observed for field 2, where a blanket weed control treatment was recommended in the current application way, with only 58% of the area treated under SS_econ_grp and 68% under SS_econ_spcs in SSWM. Although savings potential with SSWM was not evident at every field in this study, adapting herbicide use to the in-field weed distribution offers benefits. In fields with low overall weed densities but several hotspots with high weed densities, like field 1, patch spraying can help to reduce weed competition. Nevertheless, the integration of economic threshold concepts into SSWM is limited by the calculation of weed control costs, which are often determined at the field level. Also, the calculation of economic efficiency should consider the size of the area to be treated in an SSWM, for which it makes economic sense to apply a weed control treatment.

Even though the economic thresholds are developed as user-friendly approaches, they are still limited by the effort and expertise required for weed detection in the field and therefore receive only limited adoption by farmers. Future automatic weed detection and classification using unmanned aerial vehicles or ground-based sensors will make adopting of the presented concept much easier. This involves the automated collection of images (for example, using UAVs) and the development of precise, species-specific image classification, making SSWM more practical in the future. Although early-stage weed classification remains difficult, improving this will enhance the accuracy and profitability of SSWM over time (Hasan et al., 2021).

In addition, arable cropping systems are subject to constant economic changes, and input variables, like crop, yield quantity, commodity prices, herbicide prices, and spraying cost, vary over time (Keller et al., 2014). Both economic threshold concepts would therefore profit from a constant adaptation of the input variables. However, the SS_econ_grp concept was not revised since the development in the eighties. In addition, weeds are often distributed in spatial patches, and collecting weed densities only at a few sampling points in the field could result in overlooking patches of weeds. Also, the concept SS_econ_grp does not consider the weed-weed intraspecific competition (O'Donovan, 1996). The treatment recommendations solely consider weed control with herbicides, as both SS_econ_grp and SS_econ_spcs were developed based on costs related to herbicide application. Other management costs would need to be incorporated into these concepts for non-chemical weed control approaches, such as mechanical weeding.

Functional Trait-Based Decisions

The two aggregated (dis-)service distribution maps created by the concept SS_trait_spcs can provide the basis for designing SSWM concepts that incorporate both beneficial and adverse weed functional traits. The area to be treated was lower based on this functional trait-based concept for most study fields compared to the economic concepts SS_econ_grp and SS_econ_spcs. Also, at field 4, in about 40% of the field, only the service potential was above the threshold (of 0) in the scatterplot (relation between service and disservice potential; Figure 4.6 (a)), and the disservice potential was below. These area of the field will be treated based on the decisions made regarding the economic threshold concepts. Therefore, the treatment recommendations based on the SS_trait_spcs concept could be a beneficial way to support ecosystem services while reducing the risk of yield loss. On the other hand, some parts were not treated based on the SS_trait_spcs for all fields, even though the treatment would be economically useful based on the economic concepts.

There is still potential to further develop or optimize the SS_trait_spcs concept, which mainly depends on the availability of the service and disservice trait data. Other traits describing the service (flower dimensions, odour, or color) and disservice (seeding potential, vegetative shoot, or root characteristics) potentials could improve the results, the data used in this study are commonly used to describe the competitive potential and ecological services provided by weed species (Bàrberi et al., 2018; Bosch et al., 2022; Pakeman et al., 2015; Storkey, 2006). The complexity of calculating the (dis-)service potential of a species can be illustrated by the example of the species *C. arvense*. The species *C. arvense* shows the highest links to insect families, pollinators, natural enemies of pests, and phytophages insects compared to other weed species commonly observed in winter wheat (Table 4.2). At the same time, it is a highly competitive perennial species that can form dense patches in arable fields and thus suppress annual weeds and the crop plants (Fanfarillo and Kasperski, 2021).

In addition, the weed control decisions based on this concept could be adapted to individual weed control objectives and the field-specific conditions by adjusting the threshold value in the scatter plot (Figure 4.6 (a)) or by putting emphasis on individual traits with higher priority for the user (e.g., pollinator support). If the priority for the service potential of weeds increases, the threshold in the scatter plot can be adjusted to allow for greater disservice potential. Conversely, the threshold can also be shifted accordingly to reduce the disservice potential.

While the economic concepts are well studied (Cousens, 1985; Gerowitt and Heitefuss, 1990), the SS_trait_spcs concept has not yet been tested in any field studies. In addition to the limited availability of trait data for all relevant weed species, these trait data need to be further validated by field experiments with similar conditions (e.g., same crops, management, measurement technique; Zandebasiri et al. (2023). The results of the current study showed smaller areas recommended to be treated and a higher acceptance of high densities based on SS_trait_spcs in relation to the tested economic thresholds. This confirms the assumption that the economic threshold values would increase by adding an ecological value of the weeds, and therefore also the size of the area recommended to be left untreated, as made by Bensch et al. (in Print).

To provide an adequate weed control decision, both ecological and economic aspects should be considered (MacLaren et al., 2020). Historically, the main goals in agriculture have been primarily economic, focusing on maximizing crop yields and ensuring good product quality. Many farmers still fear that the damage caused by untreated weeds outweighs their potential benefits and thus prefer a 'clean field' (Wilson et al., 2008). At the same time, ensuring sustainable productivity for future generations has been a priority for farmers (MacRae et al., 1990), which highlights the need for more fundamental changes in response to the growing scientific interest for ecosystem services provided by plants such as weeds (Esposito et al., 2023). To our knowledge, the SS_trait_spcs concept is currently the only concept that considers the ecosystem services and competitive ability of weeds in threshold concepts, which has been discussed for 50 years (Franz, 1978; Steiner, 1968).

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5. General Discussion

Site-specific weed management (SSWM) represents a promising approach to enhance the sustainability of cropping systems by targeting weed control measures to areas within arable fields that have specific weed densities. In this thesis, three studies were conducted to develop an innovative SSWM decision-making approach that could enhance beneficial ecosystem services of weeds while reducing adverse effects on crop productivity. The next chapter discusses the results of these cumulative studies, each addressing individual parts of SSWM: Studying ways to improve the precision of weed distribution maps (*Chapter 2*), developing an approach to include weed functional traits in site-specific weed control decisions (*Chapter 3*), and analysing development potential of the presented approach through comparison with conventional decision-making tools (*Chapter 4*). In conclusion, the impact on SSWM and its practical implementation are discussed.

5.1. Creating Weed Distribution Maps

Understanding the weed distribution facilitates the integration of decision concepts for weed control as outlined in *Chapter 3* and *Chapter 4*. The accuracy of SSWM is highly dependent on knowledge about weed distribution in arable fields. Consequently, the study in *Chapter 2* identifies the optimal combination of sampling grid design and spatial interpolation techniques to predict accurate weed distribution maps. Out of the six tested interpolation methods, the Kriging variations (Ordinary Kriging, Simple Kriging, and Universal Kriging) produced the best results in predicting weed densities compared to the other interpolation methods for all study fields, showing minimal difference among the Kriging variations. When comparing different grid designs (random arrangement, regular arrangement, and a fine grid representing the combination of both grid types), the combination of the fine grid and Kriging interpolation methods provided the best representation of the actual weed distribution and density for most weed species and fields in this study.

Kriging assumes stationarity and linearity in the data, meaning that the spatial distribution of the variable remains constant and linear across the entire study area. Since the spatial structure of the weed distribution is not continuous, this can lead to inaccuracies in predicting weed densities. The results of this study confirm the smoothing effect of predicted weed densities, resulting in predictions of lower maximum and higher minimum weed densities for the study fields compared to the actual measured weed densities (Dille et al., 2003; Hamouz et al., 2006; Rew et al., 2001). An alternative interpolation method based on Gaussian copulas was tested to address the challenge of smoothing associated with interpolating weed densities. However, the results of this study do not confirm any improvement in weed spatial prediction, as the weed densities were similarly smoothed. Furthermore, the method's greater complexity requires substantially more computational power, which limits its practical application.

An over- and underestimation of the actual weed densities caused by smoothing can be critical for SSWM, mainly if weed control decisions are based on fixed weed control threshold levels (Backes and Plümer, 2003), as discussed in *Chapter 4*. Although the smoothing effect has been well studied, its impact on the practical implementation of SSWM is not widely discussed. The smoothing effect could be particularly problematic for weed species with high competitive ability and, therefore, a low economic control threshold value, like *Galium aparine*. As low weed density values are often predicted to be higher when interpolated due to the smoothing effect, the economic threshold value of 0.1–0.5 plants m^{-2} for *G. aparine* was even reached in areas where no individuals of the weed species were observed in the study presented in *Chapter 2*.

The difference between weed sampling for a single field-wide weed control decision and SSWM is clear: while estimating the average weed density of a field is sufficient to determine if a field-wide weed control (e.g., blanket herbicide application) is viable, SSWM requires high-resolution information on the spatial weed distribution. The results of this study indicate that weed sampling techniques using sampling grids and spatial interpolation techniques for the creation of weed distribution maps still holds potential for improvement. Areas of interest include combining the strengths of two interpolation methods, such as the simplest method with the lowest smoothing effect (Nearest Neighbor) and the more complex interpolation methods that exhibit the lowest error values in prediction (Kriging).

The weeds in this study cover a gradient of possible weed distribution pattern in winter wheat. Nevertheless, repeating this study in other crops and regions could be beneficial to validate the results under varying environmental field conditions. Weed distribution varies depending on crop type, soil cultivation, and management (Gerowitt and Heitefuss, 1990). Predicting the weed distribution could be enhanced by incorporating these variables through multivariate geostatistics and integrating additional factors that describe the location, such as soil characteristics or farming management parameters (e.g., crop rotation, seeding rate, and date; (Pätzold et al., 2020).

5.2. Recommendations Based on Species-Specific Functional Traits

After analyzing the in-field weed distribution, the knowledge about weed densities needs to be translated into weed control decisions. Weed control maps are used in an offline approach to define spatial areas in the field where a weed control treatment is beneficial for sustaining high crop quality and quantity. Currently, weed control decision concepts primarily focus on the economic profitability of weed control treatments, despite numerous studies highlighting the importance of considering the ecosystem services provided by weed plants (Blaix et al., 2018; Esposito et al., 2023; Fanfarillo and Kasperski, 2021; Franz, 1978; Steiner, 1968). The approach presented in *Chapter 3* is the first published concept to incorporate weed functional traits related to both the beneficial ecological functions (service potential) and negative impacts (disservice potential) of weeds into decision-making for SSWM. Based on the presented approach, the service potential provided by the observed weeds can be considered separately from their disservice potential in the experimental field. Specifically, 60% of the field showed high service potential, while 34% exhibited high disservice potential. The area of the field, with both high service and disservice, was 32%.

The relation between service and disservice potential was used for the decision-making and can be adapted to the user's objectives: If the priority for the service potential of weeds increases, the threshold can be adjusted to allow for greater disservice potential, and *vice versa*. Two variations of the presented approach were tested in *Chapter 4*: one aimed at reducing economic risk by recommending treatment for areas with high disservice potential (regardless of their service potential); the other focused on conserving the beneficial services provided by weeds. For all five study fields, the area recommended for treatment was about half as large when the focus shifted from primarily reducing disservice potential to primarily preserving service potential. If the area with high service potential is recommended not to be treated regardless of the high disservice potential, species like *Cirsium arvense* would be tolerated due to their high links to insects, pollinators, natural enemies of pests, and phytophagous insects. This is despite the fact that it is a highly competitive perennial species capable of forming dense patches in arable fields, which can suppress both annual weeds and crop plants.

Nevertheless, new environmental regulations to promote biodiversity can increase the tolerance of more disservice potential if the service potential can be preserved. For example, the eco-schemes, as part of the European Green Deal, are agri-environmental measures designed to financially reward farmers who voluntarily adopt environmentally friendly practices that go beyond the baseline legal requirements.

The functional trait data included in the study of *Chapter 3* were commonly used in studies describing the service and disservice potential of weeds (Bàrberi et al., 2018; Bosch et al., 2022; Pakeman et al., 2015; Storkey, 2006; von Redwitz et al., 2025). Adding further trait data for the service (e.g., supporting soil microbiome, flower dimensions, odour, and colour) and disservice potential (e.g., plant morphology, vegetative shoot, seed production, and root characteristics) could refine the impact of weed species on crop productivity or the potential to provide ecosystem services. By now, the availability of published trait data limits the practical applicability and further development of the presented concept. As trait values vary depending on management practices, crop species, site-specific conditions, assessment methods, and spatial distribution of weeds (Jørnsgard et al., 1996), a set of different trait data should ideally be collected in the same field experiment.

Normalizing trait data is a necessary step in this approach, as it facilitates the comparison of relative weed (dis-)service traits across varying units and scales. Since only the trait data for the weed species observed in the field were used in *Chapter 3*, the results provide an overview of the distribution of service and disservice potentials for this specific field. To apply this approach for comparison of the (dis-)service potential within different winter wheat fields, a trait survey and subsequent normalization for all species relevant as weeds in winter wheat under typical German growing conditions were conducted in *Chapter 4*. While the studies in *Chapters 3* and *4* were conducted in a field with weed species that had available trait data, the research revealed a lack of trait data for many other weed species. In the future, implementing this approach in practice requires a reliable and solid data foundation. Additionally, it offers many possibilities for further development, including weighting traits differently based on their significance to the user, protecting red-list weed species, managing herbicide resistance, and safeguarding fauna through the targeted promotion of weeds linked to these species.

Overall, the developed approach can be a crucial step in decision-making between creating weed distribution maps and applying weed control treatments. For future work, this concept should be tested in field studies across multiple sites and over the years, and it should be further developed for application in other crops.

5.3. Comparison of Weed Control Decision Concepts for SSWM

Decision support concepts are an integral part of SSWM, estimating the need for weed control and selecting the right spatial areas for weed control treatments. In *Chapter 4*, the approach presented in *Chapter 3* was compared to the current approaches used in weed control decision concepts: fixed economic thresholds based on weed taxonomic groups and economic thresholds based on species-specific decisions. Based on these concepts, weed control maps were created for five winter wheat fields in Germany, showing areas recommended for treatment with herbicides or left untreated for SSWM.

Unlike the concept presented in *Chapter 3*, the two economic threshold concepts were developed for field-wide decision-making, rather than for SSWM. If the economic threshold concepts were applied to the mean density values of the sampled data without regarding the spatial distribution, weed control treatments were recommended for all study fields except one. For the field without a recommendation for weed control, the mean weed density over the sampling grid did not reach the economic threshold for any weed taxonomic group or weed species. Using the economic thresholds for the SSWM approach, the weed densities reached the threshold values in about 60% of the field, resulting in treatment recommendations. Only for one site did the SSWM decision result in higher savings in herbicide use, with about 30–40% of the area recommended to be left untreated based on economic decisions. Compared to the field-wide application, the greater herbicide saving potential of integrating economic threshold concepts into SSWM, as observed in studies by Nordmeyer et al. (2003) and Keller et al. (2014), is only confirmed for one site in the study presented in *Chapter 4*. Even though the saving potential was not evident for all study sites, integrating economic thresholds in SSWM particularly benefits fields with uneven weed distribution, generally low weed densities, and punctual weed hotspots.

The simple adaptation of economic thresholds in SSWM is limited by the pixel-by-pixel calculation of weed control costs, which are currently determined at the field level. Additionally, the calculation of economic efficiency should consider the size of the area to be treated in SSWM, where it is economically viable to apply a weed control treatment. In the context of weed mapping, the fixed economic control thresholds are limited by interpolation-induced smoothing effect, as discussed in *Chapter 2.* The smoothing effect has less impact on the novel approach presented in *Chapter 3*, focusing on the weed composition and their functional traits in the arable field. Furthermore, the input data used to calculate the economic thresholds should be continuously updated to reflect ongoing economic changes, such as commodity prices, herbicide prices, and spraying costs. However, the input data and calculations have not been revised since their development of the economic thresholds in the eighties (Keller et al., 2014).

The two economic thresholds recommended weed control based on similar economic factors, such as the weed species or weed group yield loss potential, weed control costs, product price, and market value of the crop product. Therefore, both concepts recommended similar areas to be treated in the final maps. Comparing the economic threshold concepts with the novel approach presented in *Chapter 3* demonstrates the differences in weed control recommendation maps by considering the functional traits of weeds. Field areas with weed densities of *Viola arvensis* exceeding the economic thresholds were left untreated, based on the concept outlined in *Chapter 3*. The species *V. arvensis* has many links to direct feeding birds and a more extended flowering period than other weed species in winter wheat. This result shows the potential to preserve essential ecosystem functions of weeds by including functional weed traits in weed control decisions. The potential improvement of this novel concept by adding additional traits is also discussed in this study: areas with high *Alopecurus myosuroides* densities were partly left untreated. The species is a very competitive grass weed, which has the potential to produce a large number of seeds, grows rapidly, and can cause considerable yield loss (Zeller et al., 2021). These traits were not included in the calculation of the disservice potential, but are partly described by the economic threshold used to describe the weeds' potential of adverse effects on the yield quality and quantity. To conclude, the results of this thesis demonstrate that decision-making approaches could be improved by taking economic and ecological factors of controlling weeds into account.

While the economic thresholds were developed based on costs related to herbicide application, the novel approach based on weed functional traits could also be applied to other methods, such as mechanical weed control. Site-specific mechanical weed control reduces the disadvantages of field-wide treatment, such as soil disturbance, impacts on soil fauna, and risks to ground-nesting birds (Reuter et al., 2025). Weed control maps form the basis for treatment and reflect the weed composition in the field (*Chapter 3*); therefore, weed detection and control need to be conducted as two separate steps (offline approach).

5.4. Future Adaptability: Implementing Functional Traits of Weeds into SSWM

The results of this thesis confirm that SSWM has high potential to enable more productive and sustainable weed management through more resource-efficient herbicide applications. Despite the abundance of available technologies for SSWM, their practical implementation appears low (Fernández-Quintanilla et al., 2018). A study summarizes the most critical factors for adopting new approaches, such as SSWM, including perceptions of utility, farm size, level of education, and practical operability (Rasmussen et al., 2019). The initial investments associated with advanced agricultural technologies, such as spot sprayers, autonomous robots, or UAVs, may become increasingly economically viable in the future, driven by market expansion, higher affordability, and supportive policy measures (Vijayakumar et al., 2025).

Furthermore, the feasibility of SSWM is currently limited by the complexity of mapping diverse weed populations under field conditions (Vijayakumar et al., 2025). In theory, manual weed mapping serves to create weed distribution maps. Nevertheless, manual weed sampling is labor-intensive, time-consuming, expensive, and requires good knowledge of weed seedling identification (Wiles and Schweizer, 1999). The monetary savings from reduced herbicide use must offset the additional costs of weed sampling, data processing, and site-specific application technology in the long term (Wagner, 2020). Since weed distribution maps form the basis of offline SSWM, more automated weed detection systems (e.g., image recognition algorithms using UAV images) could enhance practical application. The image recognition algorithm should identify weed plants in their early developmental stages to prevent yield reduction and maintain product quality through timely treatment (Wang et al., 2024). Particularly for wheat, distinguishing crop plants from grass weeds is challenging due to the minimal differences in colour and spectral characteristics during their early growth stages (Liu et al., 2024; Wang et al., 2024). The automatic sensor system must identify weeds at the species level to integrate weed functional traits that describe the (dis-)service potential in the field based on weed composition (*Chapter 3*). However, capturing features linked to weed species using UAV images is even more challenging in densely sown crops, such as cereals, with narrow row spacing (Anderegg et al., 2023). Reducing UAV flight altitude may enhance weed detection but restrict full-field monitoring, given battery limitations and the need to handle large data volumes (Anderegg et al., 2023; Pflanz et al., 2018). Utilizing SSWM requires maps of weed distribution across the entire field, which is hindered by the low flying altitude. Overall, as the results of *Chapter 2* indicate, using grid sampling in combination with interpolation carries the risk of overlooking small weed patches between sampling grid points.

Another barrier to the practical implementation of SSWM is the concern of farmers about additional control requirements due to persistent weed infestations in untreated areas. However, a study by Christensen et al. (2003) showed no increase in weed density after five years of SSWM. Another study observed a significant increase in the infestation of some weed species in the fourth experimental year compared to the blanket treatment (Hamouz et al., 2013). Therefore, additional long-term studies are necessary to understand the dynamics of weed populations in both areas with and without weed control treatment. Any potential future costs arising from these developments should be factored into the overall evaluation. To make SSWM with novel technologies useful, all steps – from monitoring, data analysis, and data transformation to weed control treatment – should be sustainable, profitable, and easy to handle. The system needs to be robust in various field conditions and not require intensive maintenance.

The long-term effects should be tested in field studies over multiple years, especially when integrating novel decision concepts presented in *Chapter 3*, which includes weed functional traits. These experiments should not only consider the effect on crop yield, following weed infestation, population dynamic effects, and work effort, but also assess the positive effects on biodiversity. Recognizing the ecosystem services weed species provide necessitates a paradigm shift in how weeds are perceived; not merely as competitors to crops, but as potential contributors to agroecosystem functionality. To align with the environmental objectives outlined in the European Green Deal, conventional weed management strategies must be re-evaluated and adapted to promote greater biodiversity within arable systems. The reduction of herbicide use through novel strategies, such as SSWM, should be combined with further adaptations in management strategies, including higher crop rotations, varying sowing dates, and increased crop sowing densities, to promote greater weed diversity in the future.

5.5. References

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6. Supplemental Material

6.1. Chapter 2

The following section contains the supplements for *Chapter 2*.

Table S1: Patchiness Index (*PI*), Variogram function type (Sph= shperical, exp= exponential, gau= Gaussian, mat= matern family, ste= Matern stein's parameterization), and best power value *u* for all observed weed species at the study fields 1 – 4 and different sampling grid distributions (regular, random, and fine).

Grid type	Field	Weed species	Patchiness Index (*PI*)	Variogram type	Best power value *u*
regular	Field 1	*A. myosuroides*	3.30	Ste	0.50
		Matricaria spp.	0.03	Ste	2.00
		M. arvensis	8.51	Gau	2.00
		P. rhoeas	3.80	Sph	2.00
		P. aviculare	3.30	Gau	2.00
		S. officinale	-0.70	Sph	2.00
		V. hederifolia	-0.50	Ste	2.00
		V. arvensis	5.20	Ste	0.50
		Vicia spp.	8.50	Ste	2.00
	Field 2	*A. myosuroides*	-0.60	Ste	2.00
		A. arvensis	2.30	Sph	2.00
		C. bursa-pastoris	-0.70	Ste	0.50
		Cerastrium spp.	1.40	Ste	2.00
		Arbidopsis spp.	0.03	Gau	2.00
		L. amplaxicaule	4.40	Gau	2.00
		L. purpureum	26.70	Ste	0.50
		Lamium spp.	-0.60	Ste	0.50
		Matricaria spp.	2.70	Ste	2.00
		M. arvensis	-0.70	Ste	2.00
		P. rhoeas	-0.50	Gau	2.00
		P. tanacetifolia	5.80	Ste	0.50
		P. annua	1.20	Ste	0.50
		S. media	3.30	Gau	0.50
		T. arvensis	2.30	Ste	0.50
		V. persica	8.50	Ste	0.50
		V. arvensis	1.80	Ste	2.00
	Field 3	*A. myosuroides*	1.80	Ste	2.00
		M. chamomilla	1.30	Ste	0.50
		P. rhoeas	0.03	Ste	0.50
		P. aviculare	1.40	Ste	2.00
		T. inodorum	12.70	Ste	2.00

		V. hederifolia	2.60	Ste	2.00
		V. arvensis	0.03	Ste	0.50
	Field 4	*A. myosuroides*	1.80	Gau	2.00
		C. arvense	5.90	Ste	2.00
		Matricaria spp.	2.60	Ste	0.50
		P. aviculare	4.10	Ste	2.00
		V. arvensis	-0.70	Ste	0.50
random	Field 1	*A. myosuroides*	2.80	Ste	2.00
		Matricaria spp.	2.60	Ste	2.00
		M. arvensis	0.03	Sph	2.00
		P. rhoeas	1.40	Ste	2.00
		P. aviculare	0.80	Ste	2.00
		S. officinale	13.00	Sph	2.00
		V. hederifolia	-0.50	Ste	0.50
		V. arvensis	6.50	Sph	0.50
		Vicia spp.	5.90	Ste	2.00
	Field 2	*A. myosuroides*	2.60	Ste	2.00
		A. arvensis	-0.60	Gau	2.00
		C. bursa-pastoris	9.60	Ste	0.50
		Cerastrium spp.	5.50	Ste	2.00
		Arbidopsis spp.	-0.60	Ste	2.00
		L. amplaxicaule	4.70	Gau	2.00
		L. purpureum	2.60	Ste	0.50
		Lamium spp.	-0.50	Ste	0.50
		Matricaria spp.	1.40	Ste	2.00
		M. arvensis	1.60	Sph	2.00
		P. rhoeas	10.40	Ste	2.00
		P. tanacetifolia	7.00	Ste	0.50
		P. annua	0.90	Ste	0.50
		S. media	2.30	Gau	0.50
		T. arvensis	-0.60	Ste	0.50
		V. persica	1.60	Ste	0.50
		V. arvensis	1.90	Gau	2.00
	Field 3	*A. myosuroides*	0.70	Ste	2.00
		M. chamomilla	1.80	Ste	1.00
		P. rhoeas	0.03	Ste	0.50
		P. aviculare	1.20	Ste	1.00
		T. inodorum	11.20	Ste	1.50
		V. hederifolia	2.60	Sph	2.00
		V. arvensis	0.03	Ste	2.00
	Field 4	*A. myosuroides*	2.90	Ste	0.50
		C. arvense	8.50	Ste	2.00
		Matricaria spp.	0.60	Ste	0.50

		P. aviculare	3.00	Ste	0.50
		V. arvensis	2.30	Ste	2.00
fine	Field 1	*A. myosuroides*	3.00	Ste	0.50
		Matricaria spp.	3.70	Ste	2.00
		M. arvensis	9.40	Ste	0.50
		P. rhoeas	2.50	Gau	2.00
		P. aviculare	2.20	Ste	2.00
		S. officinale	8.90	Ste	2.00
		V. hederifolia	-0.70	Gau	0.50
		V. arvensis	5.90	Sph	2.00
		Vicia spp.	6.80	Ste	2.00
	Field 2	*A. myosuroides*	2.50	Gau	2.00
		A. arvensis	3.50	Ste	2.00
		C. bursa-pastoris	3.20	Ste	0.50
		Cerastrium spp.	2.50	Sph	2.00
		Arbidopsis spp.	-0.70	Ste	2.00
		L. amplaxicaule	4.50	Ste	2.00
		L. purpureum	5.90	Sph	0.50
		Lamium sp.	-0.70	Ste	0.50
		Matricaria spp.	2.20	Sph	2.00
		M. arvensis	0.80	Ste	2.00
		P. rhoeas	16.10	Gau	2.00
		P. tanacetifolia	6.10	Ste	0.50
		P. annua	1.10	Gau	0.50
		S. media	2.80	Ste	0.50
		T. arvensis	3.30	Ste	0.50
		V. persica	3.20	Ste	0.50
		V. arvensis	1.80	Sph	2.00
	Field 3	*A. myosuroides*	1.40	Sph	2.00
		M. chamomilla	12.00	Sph	0.50
		P. rhoeas	-0.50	Ste	0.50
		P. aviculare	-0.50	Ste	0.50
		T. inodorum	2.60	Ste	1.00
		V. hederifolia	1.30	Ste	2.00
		V. arvensis	1.50	Ste	0.50
	Field 4	*A. myosuroides*	2.30	Ste	0.50
		C. arvense	6.80	Ste	1.00
		Matricaria spp.	1.40	Ste	0.50
		P. aviculare	3.30	Gau	0.50
		V. arvensis	1.30	Gau	0.50

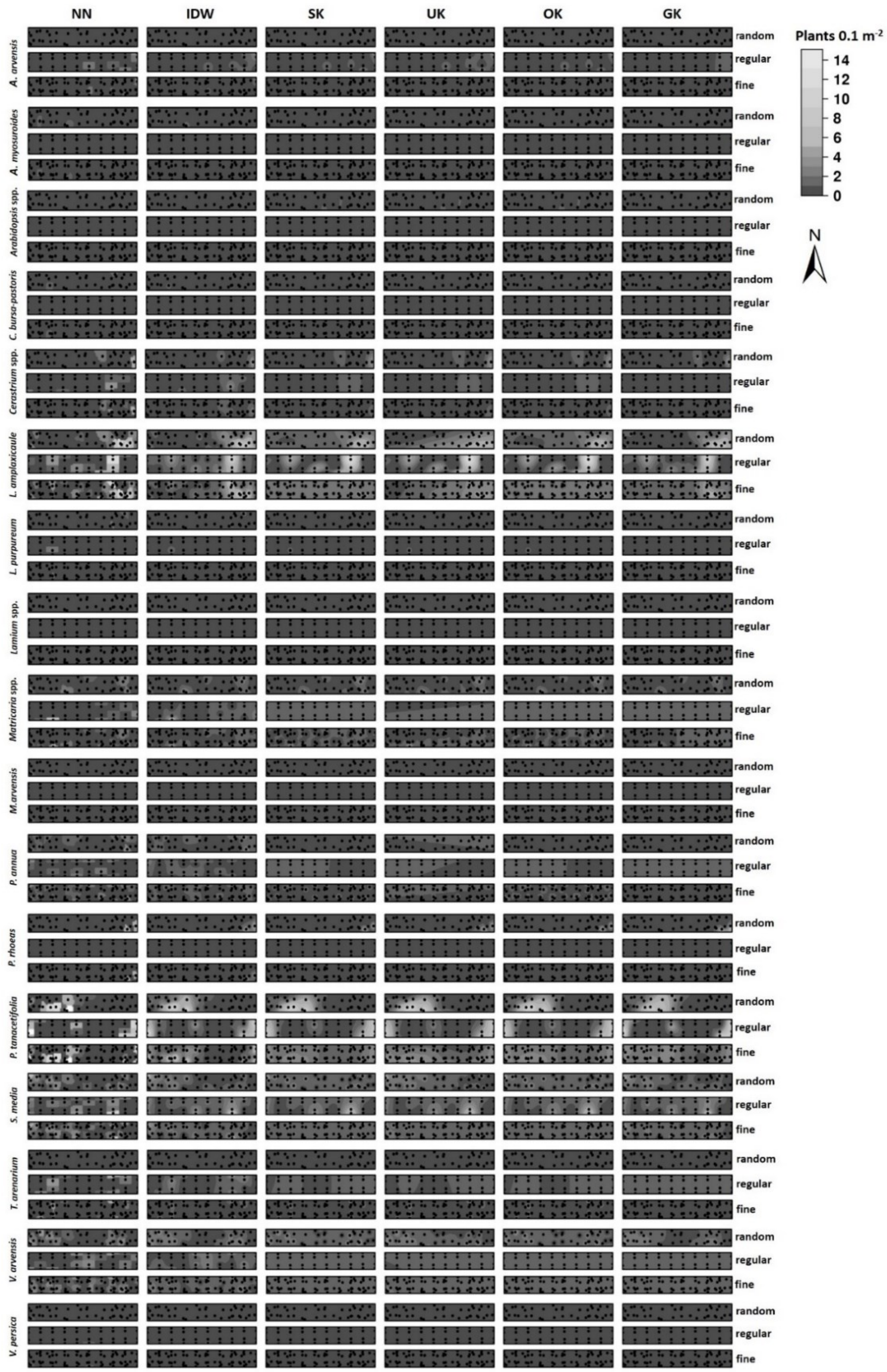

Figure S1: Predicted weed distribution (number of plants 0.1 m^{-2}) for the weed species observed at field 2 generated by six interpolation methods and on three different grid types (regular, random, and fine).

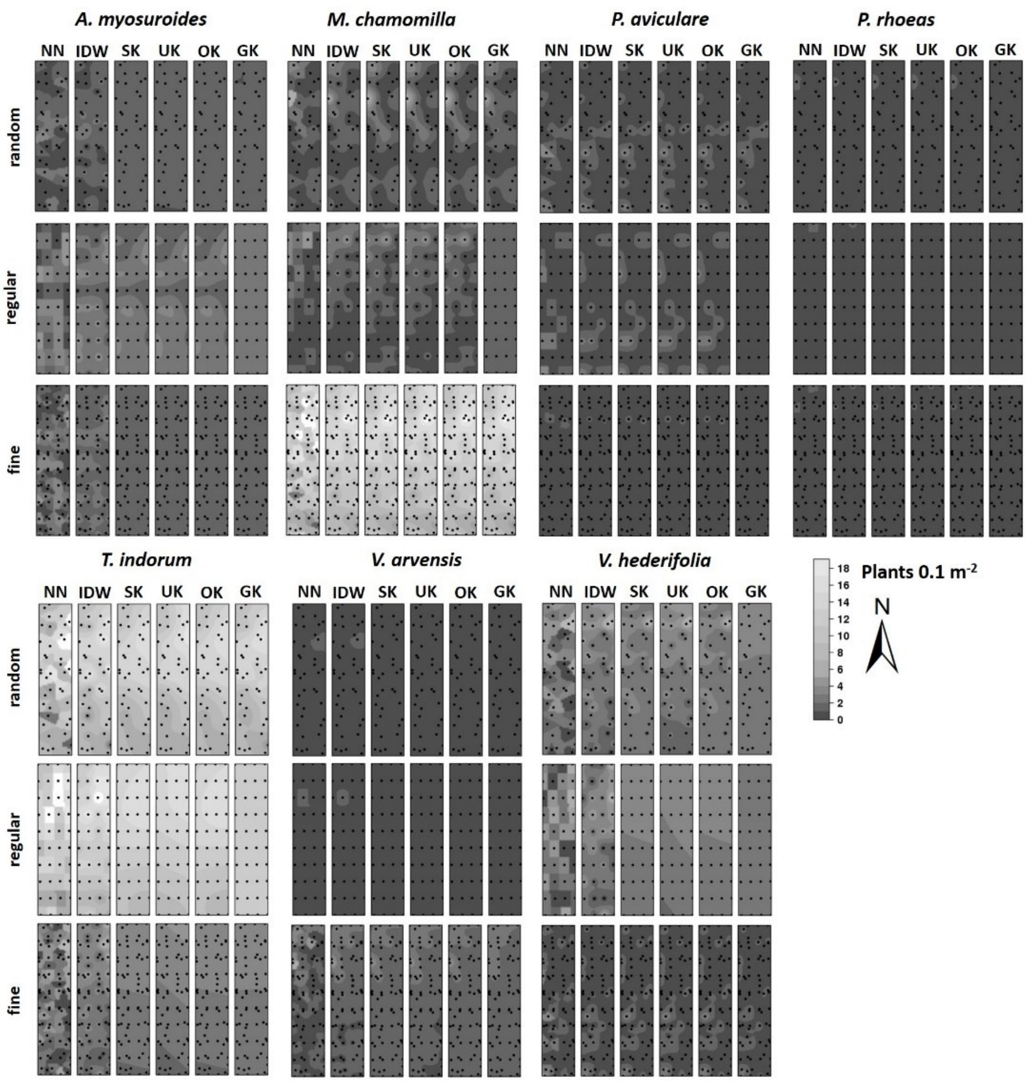

Figure S2: Predicted weed distribution (number of plants 0.1 m^{-2}) for the weed species observed at field 3 generated by six interpolation methods – Nearest Neighbor (NN), Inverse Distance Weighting (IDW), Simple Kriging (SK), Universal Kriging (UK), Ordinary Kriging (OK), and Gaussian copula Kriging (GK) – based on three different grid types (regular, random, and fine).

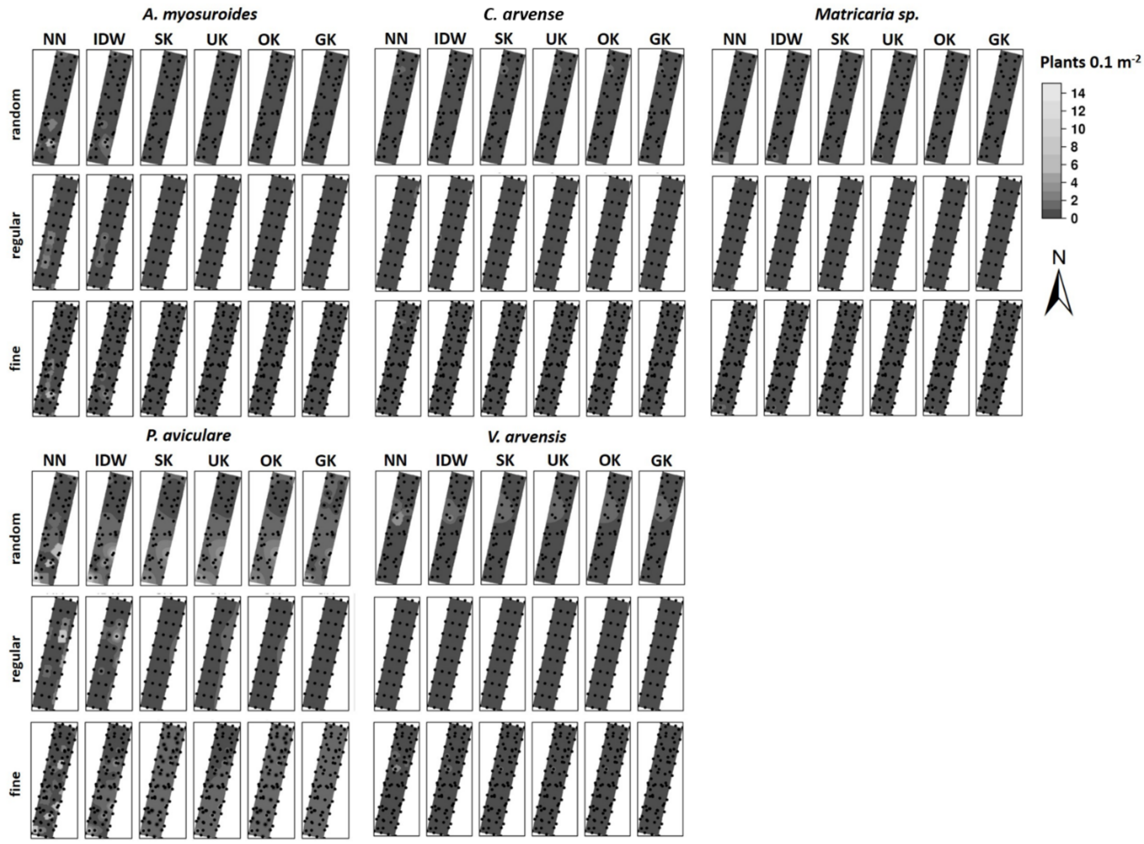

Figure S3: Predicted weed distribution (number of plants 0.1 m^{-2}) for the weed species observed at field 4 generated by six interpolation methods – Nearest Neighbor (NN), Inverse Distance Weighting (IDW), Simple Kriging (SK), Universal Kriging (UK), Ordinary Kriging (OK), and Gaussian copula Kriging (GK) – based on three different grid types (regular, random, and fine).

6.2. Chapter 3

The following section contains the supplements for *Chapter 3*.

Table S2: Leave-one-out cross-validation results for different interpolation methods.

Interpolation method	**nRMSE**
Simple Kriging	0.216
Ordinary Kriging	0.218
Universal Kriging	0.221
Inverse Distance Weighting	0.228
Nearest neighbor	0.275

Table S3: Description and Sources of the traits that were identified as Services.

Trait	Description	Source
Insect families	Number of insect families recorded on individual weed species	(Marshall et al., 2003)
Insect species	Number of insect species recorded on individual weed species	(Marshall et al., 2003)
Host specific insects	Number of insect species recorded that are dependent to the weeds to complete their life cycle	(Bosch et al., 2022)
Natural enemies	Number of named links between field weed species and natural enemies of arthropods (enemies)	(Bosch et al., 2022)
Phytophages	Number of named associations between field weed species and phytophagous arthropods (phytophages)	(Bosch et al., 2022)
Pollinator	Number of named links between field weed species and pollinators	(Bosch et al., 2022)
Birds direct	Number of named links between field weed species and Birds direct. Birds that directly feed from the weed species.	(Bosch et al., 2022)
Birds indirect	Number of named links between field weed species and Birds indirect. So Birds of prey that feed on birds directly associated with the host plant.	(Bosch et al., 2022)
Flowering duration	Duration of flowering in month	(Font, 2016)

Table S4: Description and Sources of the traits that were identified as disservices.

Trait name	Description	Source
Economic threshold	When weed density (plants/m^2) is above this economic threshold, controlling these weeds result in higher economic net returns	(Marshall et al., 2003)
Specific leaf area; SLA	Ratio between leaf area of the fresh leaf and leaf dry mass ($mm^2\ mg^{-1}$)	(Pakeman et al., 2015)
Plant height vegetative	Distance between the uppermost tip of photosynthetic tissue and the ground level	(Pakeman et al., 2015)
Pest arthropods	Number of named links between field weed species and pest arthropods	(Bosch et al., 2022)
RGRLa	Relative growth rate of green area in autumn	(Storkey, 2006)
RGRLs	Relative growth rate of green area in spring	(Storkey, 2006)

Table S5: Number of Links between the weed species and the insect families, insect species, host specific insects, phytophages, pollinators, direct and indirect birds as well as the flowering duration in month

Species	Insect families [No.]	Insect species [No.]	Host specific insects [No.]	Natural enemies [No.]	Phytophages [No.]	Pollinators [No.]	Birds direct [No.]	Birds indirect [No.]	Flowering duration [month]
M. arvensis	3.00	3.00	0.00	4.00	25.00	7.00	7.00	0.00	6.00
P. annua	15.00	53.00	7.00	3.00	150.00	16.00	6.00	10.00	12.00
P. aviculare	15.00	61.00	4.00	2.00	139.00	24.00	9.00	30.00	7.00
S. media	12.00	71.00	4.00	7.00	113.00	15.00	21.00	10.00	12.00
V. arvensis	2.00	2.00	0.00	2.00	49.00	8.00	13.00	0.00	7.00

Table S6: Economic threshold, Specific Leaf Area (SLA), vegetative plant height, Relative growth rate of the leaf in autumn (RGRLa) and spring (RGRLs) and number of links between the species and pest species

Species	Economic threshold [plants/m^{-2}]	SLA [m^{-2} g^{-2}]	Plant height vegetative [m]	RGRLa [day^{-1}]	RGRLs [day^{-1}]	Pest species [No.]
M. arvensis	25.00	42.79	0.41	0.11	0.10	0.00
P. annua	20.00	75.56	0.09	0.12	0.11	4.00
P. aviculare	15.00	37.41	0.42	0.11	0.11	3.00
S. media	10.00	52.82	0.41	0.14	0.12	3.00
V. arvensis	5.00	42.28	0.60	0.06	0.07	0.00

6.3. Chapter 4

The following section contains the supplements for *Chapter 3*.

6.3.1. Weed Functional Traits

Table S7: Service and disservice trait values for each weed species relevant for winter cereals. The values are normalized to values with a range of 0–1. Missing trait data are listed as 'NA'.

Species	**Relative yield loss (wheat)**	**Relative yield loss (barley)**	**Pest species**	**Specific Leaf Area**	**Vegetative Plant Height**	**Natural enemies**	**Phytophages**	**Pollinator**	**Birds direct**	**Birds indirect**	**Insect families**	**Insect species**	**Host-specific insects**	**Flowering duration**
Aethusa cynapium	0.02	0.02	0.00	0.51	0.72	0.00	0.00	0.01	0.00	0.00	0.17	0.04	0.00	0.17
Alopecurus myosuroides	0.07	0.07	0.75	0.39	0.17	0.21	0.27	0.03	0.00	0.00	0.06	0.07	0.00	0.28
Anthemis arvensis	0.05	0.05	0.31	0.48	0.16	0.14	0.26	0.12	0.05	0.00	0.44	0.20	0.14	0.28
Apera spica-venti	0.07	0.07	0.72	0.20	0.48	0.21	0.19	0.03	0.00	0.00	NA	NA	NA	0.00
Aphanes arvensis	0.02	0.02	0.00	0.16	0.03	0.00	0.13	0.00	0.00	0.00	NA	NA	NA	0.23
Arabidopsis thaliana	0.02	0.02	0.22	0.52	0.10	0.00	0.05	0.01	0.00	0.00	NA	NA	NA	0.06
Avena fatua	0.07	0.07	NA	0.26	0.59	NA	NA	NA	NA	NA	0.11	0.06	0.14	1.00
Bromus secalinus	0.07	0.07	0.03	0.38	0.45	0.00	0.19	0.01	0.00	0.00	NA	NA	NA	0.17
Bromus sterilis	0.07	0.07	0.03	0.49	0.24	0.00	0.19	0.01	0.00	0.00	NA	NA	NA	0.06
Capsella bursa-pastoris	0.07	0.07	0.34	0.45	0.12	0.71	0.22	0.07	0.33	0.00	0.44	0.20	0.14	0.28
Centaurea cyanus	0.16	0.16	0.16	0.24	0.40	0.21	0.44	0.26	0.05	0.40	NA	NA	NA	0.23
Chenopodium album	0.00	0.00	0.19	0.27	0.72	0.21	0.22	0.07	0.95	0.57	0.78	0.43	0.29	0.17
Cirsium arvense	0.10	0.11	0.44	0.12	0.79	1.00	1.00	1.00	0.38	0.33	1.00	0.70	0.71	0.11
Convolvulus arvensis	0.02	0.02	0.41	0.41	0.28	0.43	0.46	0.07	0.24	0.40	NA	NA	NA	0.17
Elymus repens	0.10	0.10	0.09	0.30	0.79	0.00	0.28	0.05	0.10	0.00	NA	NA	NA	0.40
Equisetum arvense	0.01	0.01	NA	0.00	0.24	NA	NA	NA	NA	NA	NA	NA	NA	0.06
Euphorbia helioscopia	0.05	0.05	0.41	0.41	0.28	0.43	0.46	0.07	0.24	0.40	NA	NA	NA	0.17
Fallopia convolvulus	0.05	0.05	0.28	NA	NA	0.14	0.87	0.22	0.43	1.00	0.78	0.86	0.57	NA
Fumaria officinalis	0.05	0.05	NA	0.41	0.33	NA	NA	NA	NA	NA	0.00	0.03	0.00	0.28
Galeopsis tetrahit	0.05	0.05	NA	0.48	0.48	NA	NA	NA	NA	NA	0.28	0.17	0.14	0.23
Galium aparine	1.00	1.00	0.03	0.56	1.00	0.00	0.93	0.18	0.38	0.00	0.67	0.41	0.57	0.23
Geranium dissectum	0.05	0.05	0.09	0.29	0.31	0.00	0.14	0.02	0.24	0.83	0.06	0.01	0.00	0.17
Geranium pusillum	0.05	0.05	0.09	NA	NA	0.00	0.14	0.02	0.24	0.83	0.06	0.01	0.00	NA
Lamium amplexicaule	0.07	0.07	0.09	0.21	0.07	0.00	0.44	0.21	0.24	0.83	0.39	0.24	0.29	0.06
Lamium purpureum	0.07	0.07	0.09	0.65	0.21	0.00	0.44	0.21	0.24	0.83	0.39	0.24	0.29	0.40

Lolium spp.	0.07	0.07	0.09	0.43	0.24	0.00	0.37	0.00	0.19	0.60	NA	NA	NA	0.11
Matricaria chamomilla	0.05	0.05	0.31	0.29	0.10	0.14	0.26	0.12	0.05	0.00	0.44	0.20	0.14	0.17
Myosotis arvensis	0.07	0.07	0.00	0.43	0.19	0.29	0.12	0.07	0.33	0.00	0.11	0.03	0.00	0.28
Papaver rhoeas	0.05	0.05	0.13	0.52	0.38	0.07	0.05	0.04	0.00	0.00	0.33	0.10	0.00	0.11
Poa annua	0.01	0.01	1.00	0.59	0.00	0.21	0.95	0.15	0.29	0.33	0.78	0.74	1.00	0.63
Polygonum aviculare	0.01	0.01	0.28	0.42	0.76	0.14	0.87	0.22	0.43	1.00	0.11	0.03	0.00	0.34
Polygonum persicaria	0.05	0.05	0.22	0.35	0.40	0.29	0.36	0.06	0.52	0.73	0.78	0.86	0.57	0.11
Sinapis arvensis	0.07	0.07	0.75	0.66	0.31	0.00	0.28	0.28	0.29	0.40	0.67	0.51	0.43	0.23
Sisymbrium officinale	0.11	0.11	0.44	NA	NA	0.00	0.19	0.04	0.00	0.00	NA	NA	NA	NA
Stellaria media	0.16	0.16	0.16	1.00	0.17	0.50	0.70	0.14	1.00	0.33	0.61	1.00	0.57	0.63
Thlaspi arvense	0.05	0.05	0.31	0.32	0.19	0.07	0.07	0.07	0.29	0.13	NA	NA	NA	0.23
Tripleurospermum inodorum	0.11	0.11	0.44	0.28	0.59	0.21	0.42	0.10	0.05	0.00	0.44	0.20	0.14	0.28
Veronica arvensis	0.05	0.05	0.44	0.35	0.07	0.36	0.33	0.04	0.05	0.17	0.00	0.00	0.00	0.40
Veronica hederifolia	0.01	0.01	0.28	0.42	0.10	0.21	0.17	0.02	0.00	0.00	0.00	0.00	0.00	0.11
Veronica persica	0.05	0.05	0.44	0.67	0.17	0.36	0.33	0.04	0.05	0.17	0.00	0.00	0.00	0.63
Viola arvensis	0.07	0.07	0.13	0.32	0.12	0.14	0.28	0.07	0.62	0.00	0.06	0.01	0.00	0.34

6.3.2. Results for Sites 2, 3, and 5

Field 2

The weed distribution maps for field 2 showed that *Polygonum aviculare* (20 plants m^{-2}) and *Viola arvensis* M. (15 plants m^{-2}) exhibited the highest mean density (Figure S4). The species *V. arvensis* occurred particularly on the left edge of the field, and *P. aviculare* in the bottom of the field. *P. aviculare* showed the highest maximum density with 146 plants per m^2. The other species observed were *Myosotis arvensis* (L.) Hill, *Stellaria media* (L.) Vill., and *Poa annua* L.. These species were detected at single points with an average of less than 10 plants m^{-2}. The species *P. annua* was observed with the lowest mean density of 1 plant per m^2.

The weed distribution maps were merged with the species-specific service and disservice traits (Table S7). After plotting the service against the disservice potential in a scatter plot (Figure S4 (2a)), the pixel data can be separated into four quadrants. The study field had a total pixel number of 3128, with a pixel size of 1 m^2. For almost half of the field (49%), the service and disservice potential were below the threshold (1501 m^2; Figure S4 (2b)). Overall, 45% of the field had a high service potential (1415 m^2), and about half of the field (48%) had a high disservice potential (1506 m^2). The area ‘Q2’ accounted for 42% of the field. The service potential was above the threshold on only 3% of the field (‘Q4’).

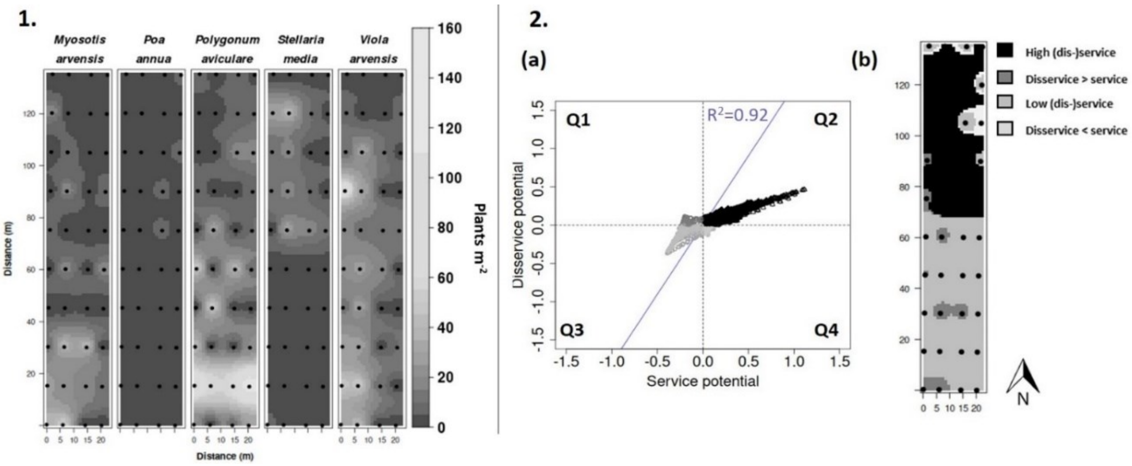

Figure S4: (1) Weed distribution maps for the species observed in field 2. (2) Correlation between the pixel values of the service and the disservice distribution maps. The Spearman correlation coefficient is shown in blue.

In the weed control map based on SS_econ_grp, approximately 43% of the field was recommended for leaving untreated (Figure S5). Based on the species-specific concept SS_econ_spcs, the untreated area was reduced by 6% (35%) compared to the decisions of SS_econ_grp. A weed control treatment was recommended primarily for the western and southern parts of the field, based on economic threshold concepts. For the concept SS_trait_spcs (focus disservice), about half (51%) of the field was recommended to be left untreated. The highest area without treatment (88%) was achieved when using SS_trait_spcs (focus service).

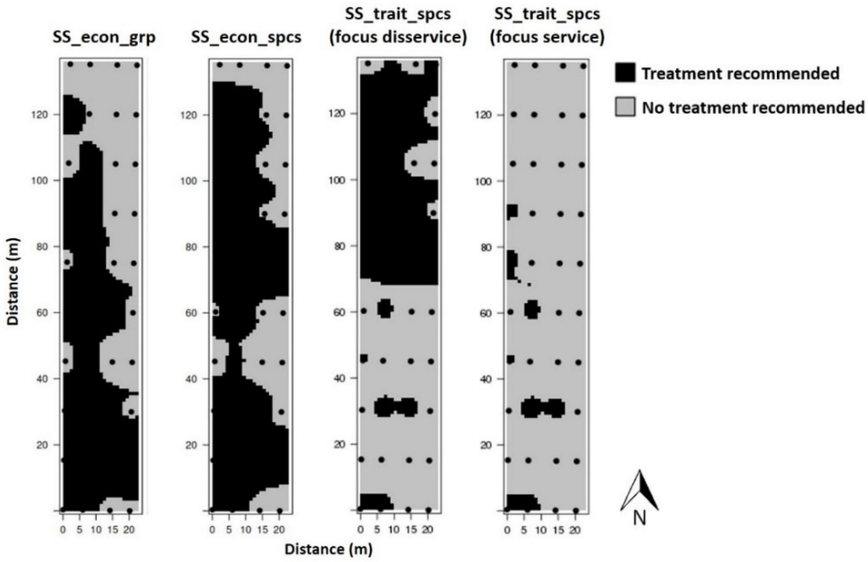

Figure S5: Weed control maps based on the different concepts for field 2.

Field 3

The mean density was the highest for *A. myosoruides* (29 plants m^{-2}) and *V. hederifolia* (31 plants m^{-2}; Figure S6 (a)) in field 3. The species with the lowest mean density were *Myosotis arvensis* (L.) Hill and *Lamium purpureum* L., with less than 0.3 plants per m^2. The maximum density was the second highest for *V. arvensis* compared to the other species (107 plants per m^2). The highest maximum plant density, 127 plants per m^2, was observed for *V. hederifolia*.

Plotting the service potential against the disservice potential in a scatterplot (Figure S6 (2a)) showed that about half of the field had a low service and disservice potential (Q3; 49%). The area in the field where the service potential exceeded the disservice potential was, with a size of 1%, the smallest. The area 'Q1' was slightly larger with a higher disservice than service potential (7%). In about 43% of the field, the service and disservice potential was higher than zero.

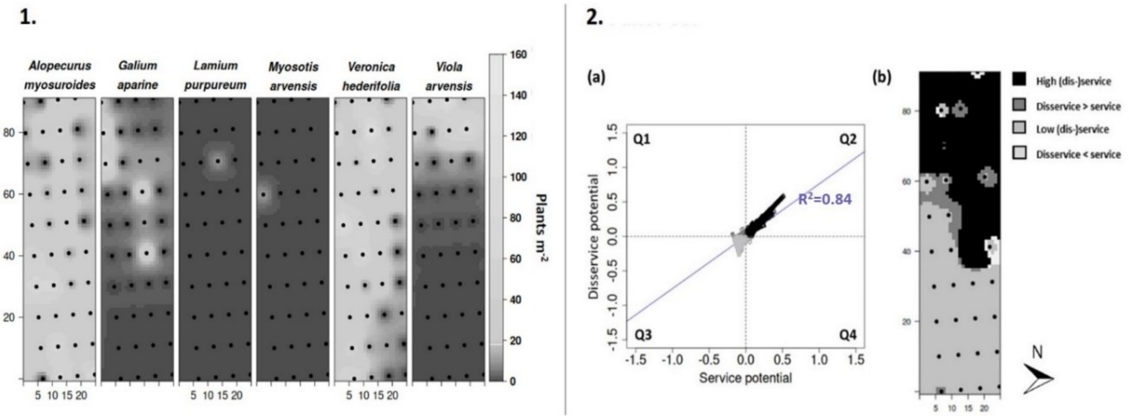

Figure S6: (1) Weed distribution maps for the species observed at field 3. (2) Correlation between the pixel values of the service and the disservice distribution maps. The Spearman correlation coefficient is shown in blue.

A weed control treatment was recommended for the entire field when using SS_econ_grp, and only 3% would be left untreated based on SS_econ_spcs (Figure S7). Considering the original application of these concepts (a single field-wide decision), the entire area would have been addressed in SS_econ_grp and SS_econ_spcs. Based on SS_trait_spcs (focus disservice), only the northern half of the field was recommended to be treated. Only treating the 'Q1' area of the field in SS_trait_spcs (focus servce), left 94% of the field untreated.

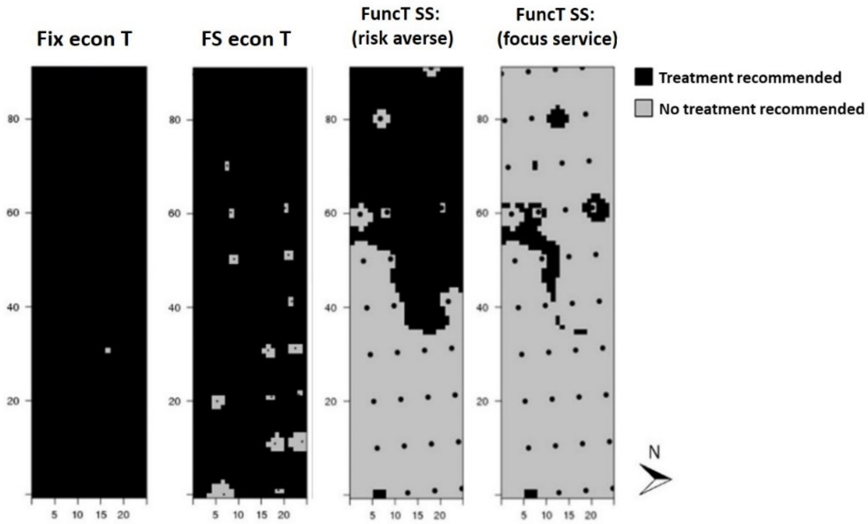

Figure S7: Weed control maps based on the different concepts for field 3.

Field 5

The species *V. arvensis* occurred in the entire field with the highest plant numbers (Figure S8 (a)). The mean density was 542 plants per m^2, and the maximum density was 1013 per m^2. All the other species, *G. aparine*, *Geranium dissectum* L., *Matricaria chamomilla* L., and *S. media*, were observed with a mean density of less than 3 plants per m^2.

In 13% of the field, the service and disservice potential was higher than zero (Q2 in Figure S8 (b)). The areas Q1 and Q4 had an area less than 5% (1% and 3%). For 41% of the field, the service and disservice potential was less than zero. The Spearman correlation between service and disservice potential was high (0.98).

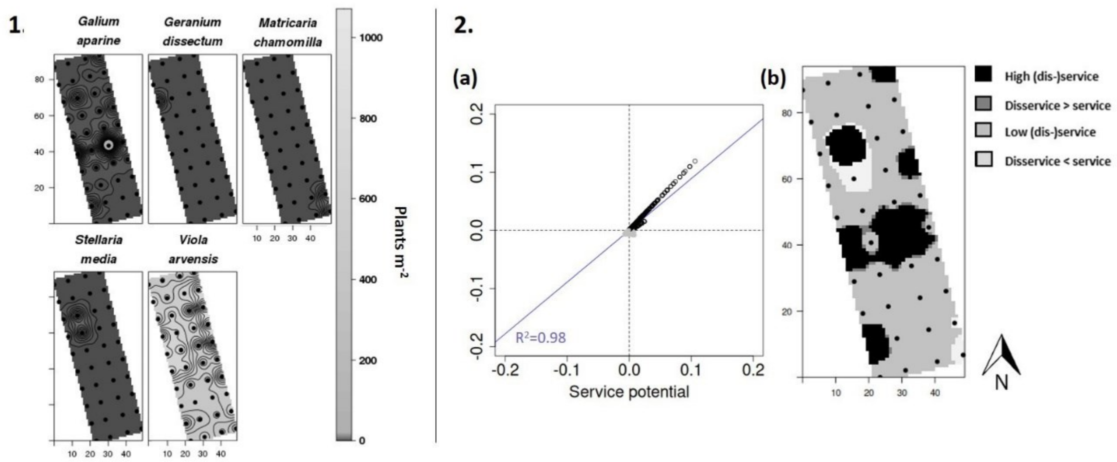

Figure S8: (1) Weed distribution maps for the species observed at field 5. (2) Correlation between the pixel values of the service and the disservice distribution maps.

For field 5, a weed control treatment was recommended for the entire field based on SS_econ_grp and SS_econ_spcs (Figure S9). Different results occur when using SS_trait_spcs: Based on the risk-averse variation (focus disservice), 56% of the area can be left untreated, and with a focus on service potential 97% of the total area was left untreated.

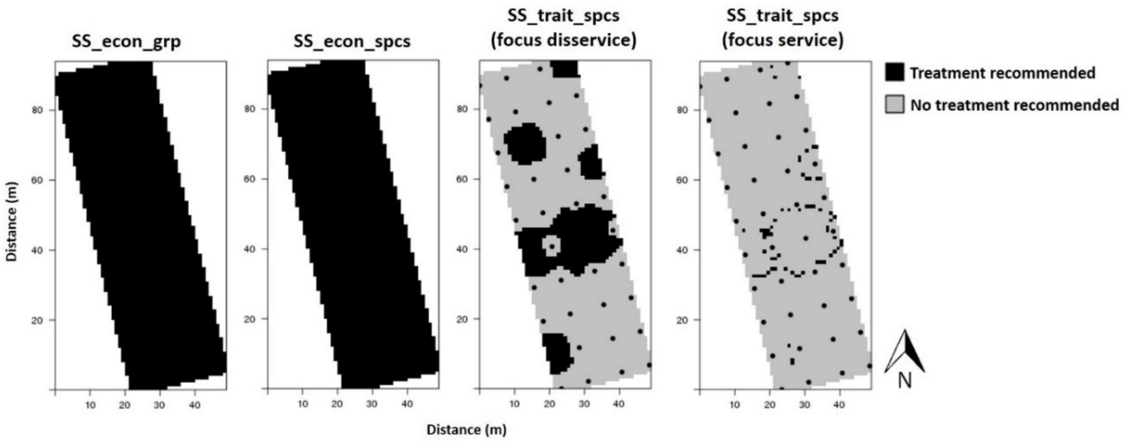

Figure S9: Weed control maps based on the different concepts for field 5.

List of Publications and Presentations

Peer-Reviewed Journal Publications

1. Schatke, M., Meier, M., Schröder, B. and Weber, S. (2022) 'Impact of the 2020 COVID-19 lockdown on NO_2 and PM_{10} concentrations in Berlin, Germany', *Atmospheric Environment* vol. 290, p. 119372, DOI: 10.1016/j.atmosenv.2022.119372.

2. Von Redwitz, C., Kämpfer, C., Hodac, L., Mäder, P., Pflanz, M., Milz, S., Rüdiger, T., Schatke, M., Ulber, L. and Wäldchen, J. (2022) 'Better-Weeds – Next generation weed management'. *Tagungsband: 30. Deutsche Arbeitsbesprechung über Fragen der Unkrautbiologie und -bekämpfung*, Julius-Kühn-Archiv. DOI: 10.5073/20220124-075254.

3. Schatke, M., von Redwitz, C., Verschwele, A., Bückmann, H., Kämpfer, C., Ulber, L. (2022). 'Site-specific weed management based on species-specific weed densities'. *IOBC WPRS bulletin.* Landscape Management for Functional Biodiversity: Proceedings of the 9th Meeting at Milan (Italy); 7-10 June, 2022.

4. Schatke, M., Ulber, L., Musavi, T., Wäldchen, J. & von Redwitz, C. (2024): 'From unwanted to wanted: Blending functional weed traits into weed distribution maps'. *Weed Research*, vol. 64, No. 6, pp. 407–417. DOI: 10.1111/wre.12664.

5. Schatke, M., Ulber, L., Kämpfer, C., von Redwitz, C. (2025). 'Estimation of weed distribution for site-specific weed management—can Gaussian copula reduce the smoothing effect?', *Precision Agriculture*, vol. 26, No. 37. DOI: 10.1007/s11119-025-10232-6.

6. von Redwitz, C., Andert, S., Bensch, J., Forster, R., Schatke, M., Strehlow, B. (2025). 'Enhancing Arable Weed Diversity by Reduced Herbicide Use?'. *Journal of Crop Health*, vol. 77, No. 65. DOI: 10.1007/s10343-025-01127-7.

7. Schatke, M., Bensch, J., Gerowitt, B., Ulber, L., & von Redwitz, C. (accepted): 'Trait-Based Weed Control Decisions Compared to Economic Thresholds for Site-Specific Weed Management'. DOI: 10.2139/ssrn.5279279.

Conference Proceedings

1. 19th European Weed Research Society Symposium (2022). 'Which interpolation method most accurately estimates weed distribution for site-specific weed control?', Athen, Greece. – *oral presentation*

2. IOBC-WPRS (2022). 'Site-specific weed management based on species-specific weed densities', Mailand, Italy (online). – *oral presentation*

3. 63. Deutsche Pflanzenschutztagung (2023). 'Verschneiden von Unkrauteigenschaften mit Unkrautverteilungskarten für das SSWM', Göttingen, Germany. – *oral presentation*

4. 63. Deutsche Pflanzenschutztagung (2023). 'Leistungsvergleich von Interpolationsmethoden für die standortspezifische Unkrautbekämpfung', Göttingen, Germany. – poster *presentation*
5. 52nd Annual Meeting of the Ecological Society of Germany, Austria and Switzerland (2023) 'Blending functional weed traits into weed distribution maps', Freising, Germany. – *poster presentation*
6. 53rd Annual Meeting of the Ecological Society of Germany, Austria and Switzerland (2024) 'Including beneficial functional traits of weeds in control strategies', Leipzig, Germany. – *oral presentation*
7. IOBC-WPRS (2024) 'Comparing threshold concepts for weed control', Pisa, Italy. – *oral presentation*
8. 20th European Weed Research Society Symposium (2025) 'Decision-making for site- and plant-specific weed management: Comparing novel approaches', Lleida, Spain – *poster presentation*

Curriculum Vitae

Education

05/2022–today	PhD Candidate, Crop Health Group, Faculty of Agriculture, Civil and Environmental Engineering, University of Rostock
10/2018–10/2021	Master of Science, Faculty of Environmental Science, Technical University of Brunswick
10/2015–10/2018	Bachelor of Science, Faculty of Environmental Science, Technical University of Brunswick

Work Experience

10/2024–today	Research Scientist, Weed Science Group, Institute for Plant Protection in Field Crops and Grassland, Julius Kühn-Institut
10/2021–10/2024	Research Assistant in „BETTER WEEDS“-Project, Weed Science Group, Institute for Plant Protection in Field Crops and Grassland, Julius Kühn-Institut
10/2018–10/2021	Student Assistance, Department for Climatology and Environmental Meteorology, Faculty of Environmental Science, Technical University of Brunswick