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From unwanted to wanted: Blending functional weed traits into weed distribution maps

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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

1 | INTRODUCTION

An intensification of farming practices accompanied by simplification of crop rotations, increased nitrogen fertilisation 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 & 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 & 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 & 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., 2023; 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., 2019). With the advent of deep learning methods, automatic species identification is achieving accuracy comparable to that of human experts (Wäldchen & 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 by mainly incorporating economic losses linked to the weed population densities and disregard the biological characteristics of the species (Gerowitt & 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 respond 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.

2 | MATERIALS AND METHODS

2.1 | 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°13′29.2″ N 10°37′49.2″ E; Figure 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. 24 m × 100 m), no herbicide treatment was carried 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 interpolation and nearest neighbour) using a leave-one-out cross-validation (Table S1). 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.

2.2 | 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; Tables S2 and S3). 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.

2.2.1 | Service traits

Nine different functional traits were used to describe the beneficial ecological functions of weeds (service traits, Table S2). 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).

2.2.2 | 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 & Heitefuß, 1990). The 'specific leaf area' represents a ratio between 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

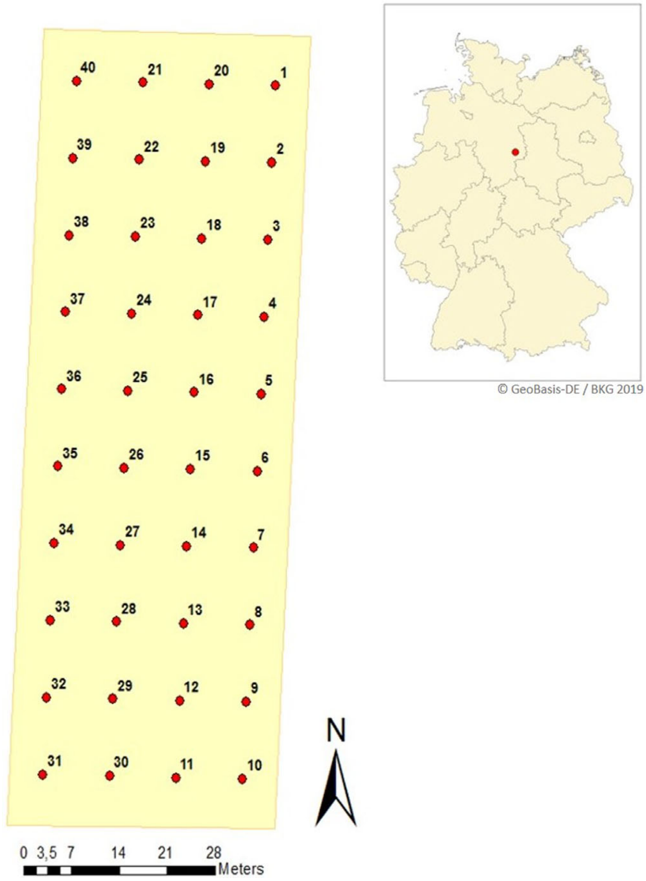


FIGURE 1 Study field in Sickte, Germany with 40 grid points for weed assessments (approx. 24 m × 100 m).

'relative growth rate of green area' in spring (RGRLs; d^{-1}) and autumn (RGRLa; d^{-1}) (Storkey et al., 2006) as well as the number of observed links between the weed species and pest arthropods ('pest species') (Bosch et al., 2022).

2.3 | Analysis

To compare the trait values within the groups of service traits (Table 1) and disservice traits (Table 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 1):

$$\mathrm{WT}_i = \frac{\sum (N_{S_i} * T_S)}{\sum No.\ Weeds_i}, \tag{1}$$

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 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 analyses were conducted using R 4.1.1 (R Core Team, 2021). The PCA was done using the RStoolbox package (Leutner 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 analyse 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 | 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 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.

TABLE 1 Normalised values for the collected service traits (see Table S2 for description of traits).

Species	Insect families	Insect species	Host-specific insects	Natural enemies	Phytophages	Pollinators	Birds direct	Birds indirect	Flowering duration
Myosotis arvensis	0.08	0.01	0.00	0.40	0.00	0.00	0.07	0.00	0.00
Poa annua	1.00	0.74	1.00	0.20	1.00	0.53	0.00	0.33	1.00
Polygonum aviculare	1.00	0.86	0.57	0.00	0.91	1.00	0.20	1.00	0.17
Stellaria media	0.77	1.00	0.57	1.00	0.70	0.47	1.00	0.33	1.00
Viola arvensis	0.00	0.00	0.00	0.00	0.19	0.06	0.47	0.00	0.17

TABLE 2 Normalised values for the collected disservice traits (see Table S3 for description of traits).

Species	Economic threshold	SLA	Plant height vegetative	RGRLa	RGRLs	Pest species
Myosotis arvensis	0.00	0.14	0.63	0.54	0.64	0.00
Poa annua	0.25	1.00	0.00	0.65	0.74	1.00
Polygonum aviculare	0.50	0.00	0.64	0.53	0.74	0.28
Stellaria media	0.75	0.40	0.63	1.00	1.00	0.16
Viola arvensis	1.00	0.13	1.00	0.00	0.00	0.13

Abbreviations: RGRLa, relative growth rate of green area in autumn; RGRLs, relative growth rate of green area in spring; SLA, specific leaf area.

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.

According to the trait analysis, the species *Poa annua* and *P. aviculare* showed the highest number of linkages with insect families (Table 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*.

The species *Poa annua* had the highest SLA and the highest number of linkages with pest species (Table 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.

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). 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.

A greater spatial heterogeneity was displayed in the distribution of the values in the trait distribution maps for the weighted disservice traits (Figure 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.

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 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

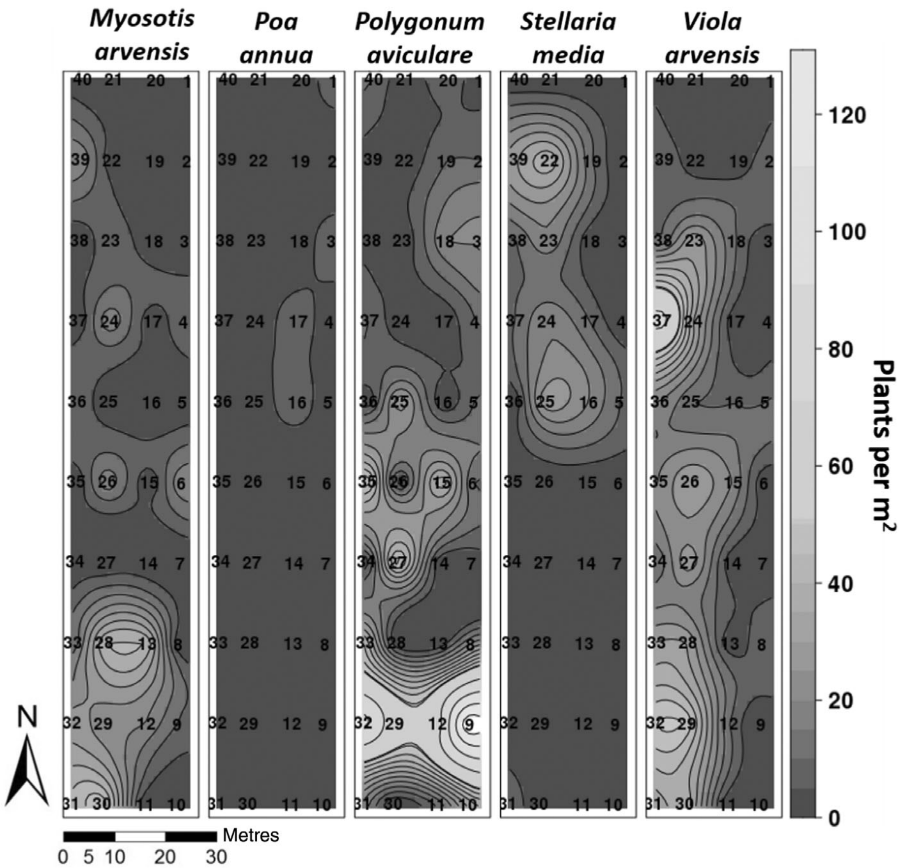


FIGURE 2 Weed distribution maps (number of individual plants m^{-2}) for the weed species observed at the study site.

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.

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 6A) 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%).

4 | 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 also 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.

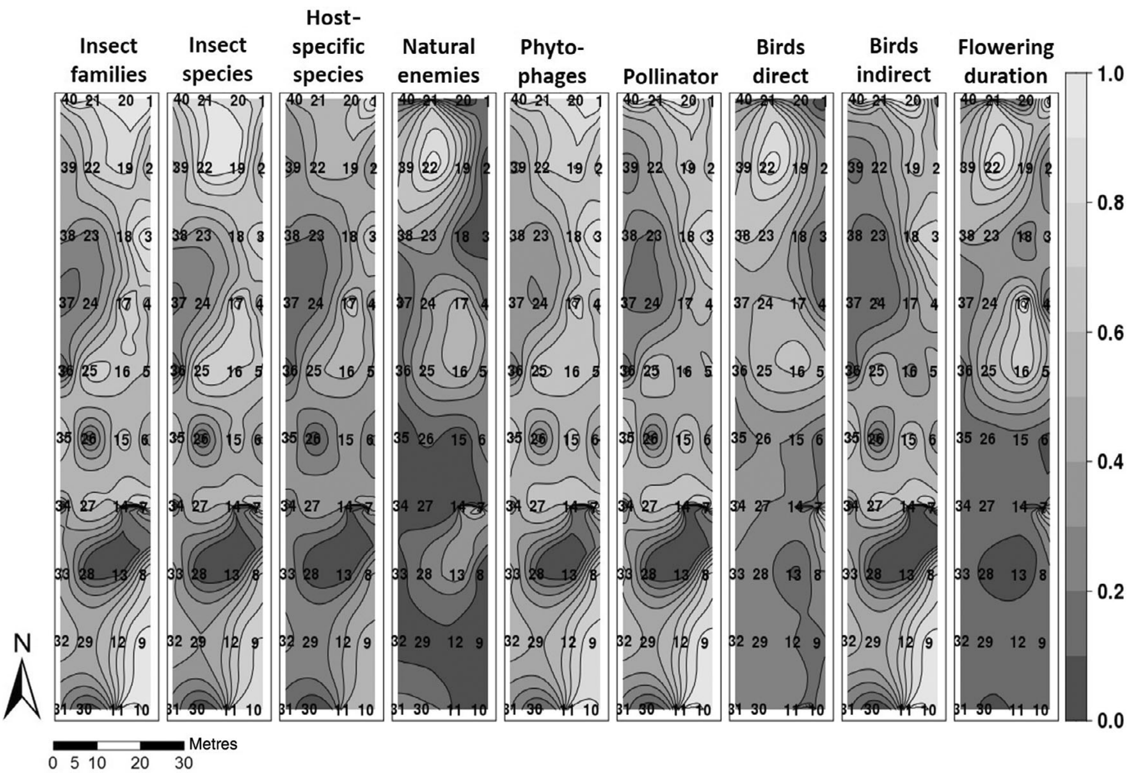
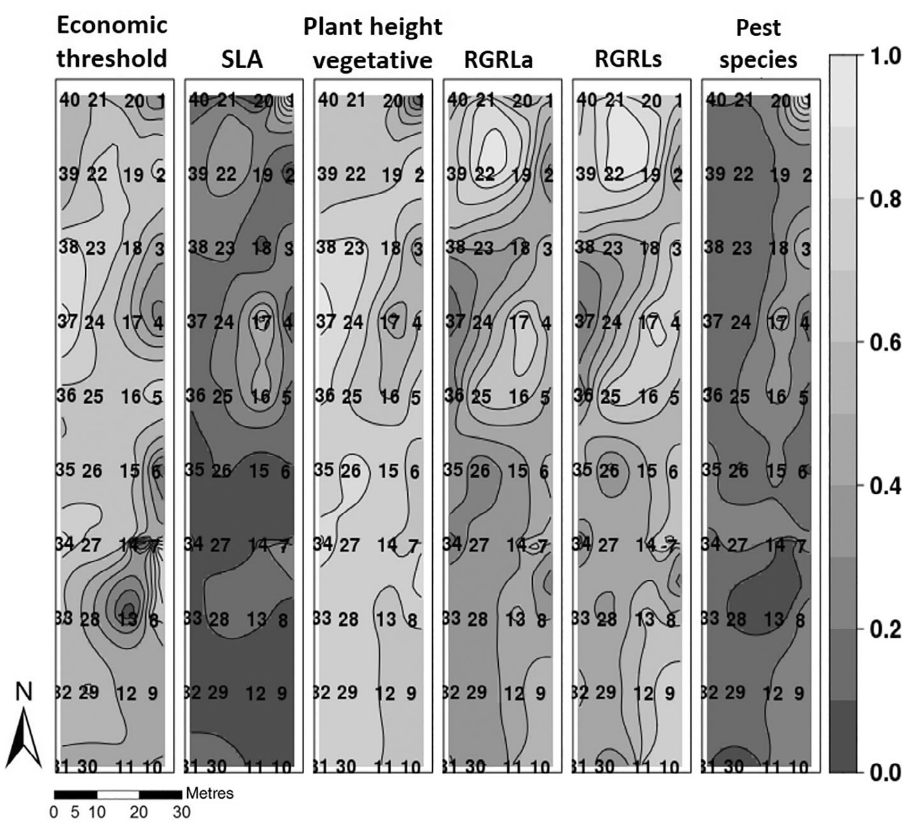


FIGURE 3 Trait distribution map for weighted values of the service traits for each grid pixel of the weed distribution map. The raster points range from #1 in the northeast to #40 in northwest.

FIGURE 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.



4.1 | 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 6A), a (dis-)service ratio field map could be created (Figure 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 31.9% 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

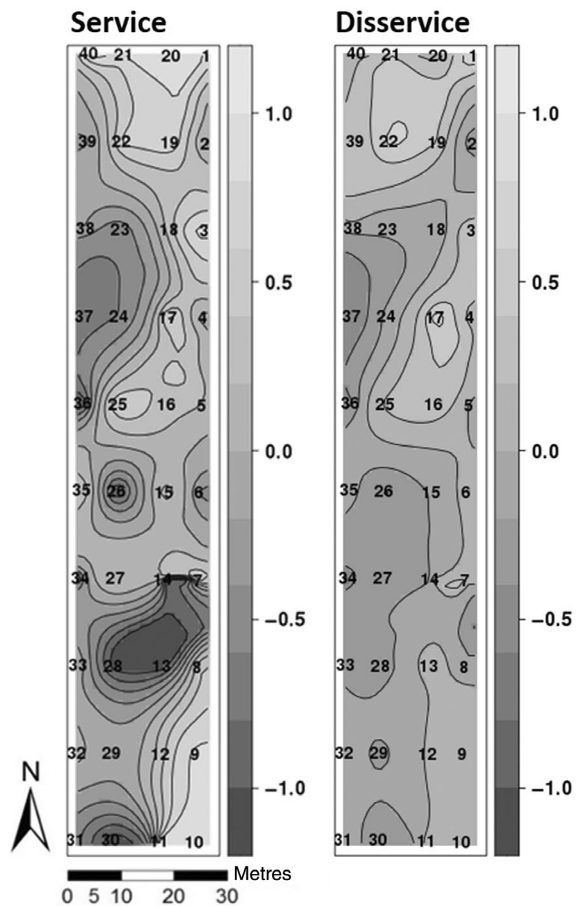


FIGURE 5 Service and disservice distribution maps in the study field showing the scores of the first axis of a PCA based on the occurrence of the weed species and the species-specific traits. The raster points range from #1 in the northeast to #40 in northwest. PCA, principal component analysis.

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.

4.2 | 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-

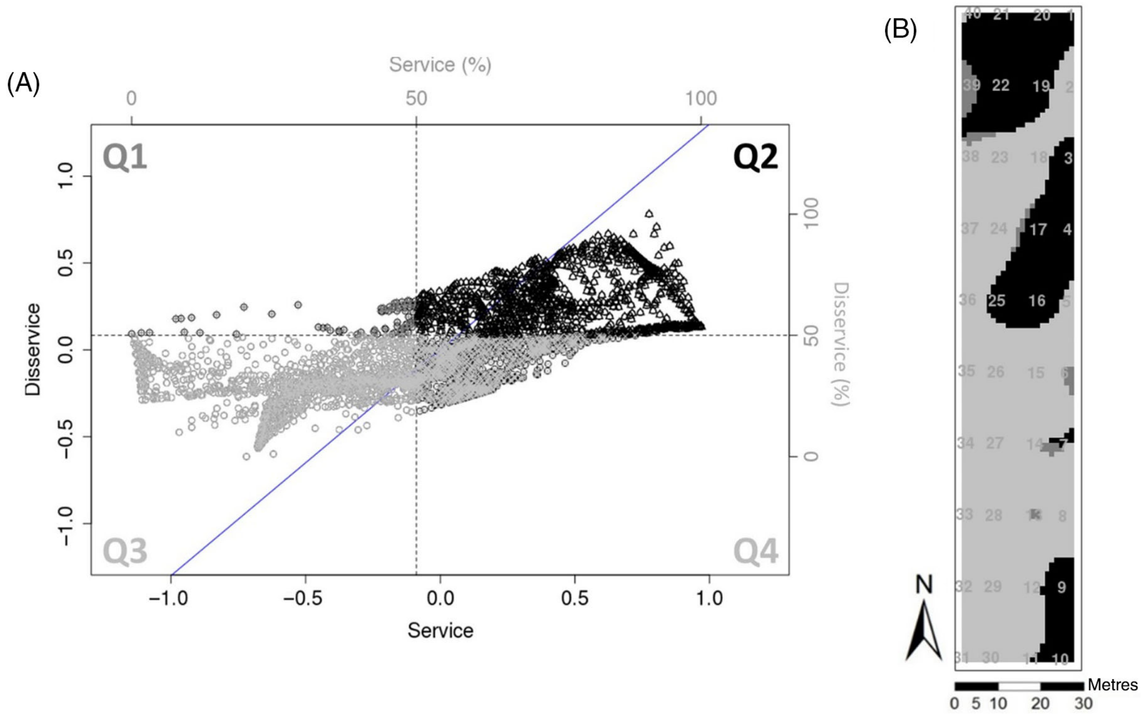


FIGURE 6 (A) Correlation between the pixel values of the service and the disservice distribution maps (Figure 5) with values from −1 (0% potential) to 1 (100% potential). The quadrant 'Q1' includes values with high disservice and low service potential, 'Q2' values with high service and high disservice potential and both 'Q3' and 'Q4' have a low disservice potential and therefore received the same colour. (B) The '(dis-)service ratio field map' was created based on the locations of the pixels in the four quadrants (A) using the same colours.

specific conditions, spatial distribution (like nests) of weeds, management practices and trait measurement method (Jørnsgård 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 & 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.

4.3 | 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 application (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 in 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 could make a statement about the potential of ecological service provided by weeds in an agricultural field. The results of this study in form of maps can also be applied to overview and visualise the service and disservice potentials on a field and even to monitor changes within a short or longer period.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data supporting the results of this study are available from the corresponding author upon reasonable request.

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REFERENCES

Bàrberi, P., Bocci, G., Carlesi, S., Armengot, L., Blanco-Moreno, J.M. & Sans, F.X. (2018) Linking species traits to agroecosystem services: a functional analysis of weed communities. *Weed Research*, 58(2), 76–88.

Bosch, N., Zhang, H. & Gerowitt, B. (2022) Ackerunkräuter in Deutschland unterstützen die Artenvielfalt von Arthropoden und Vögeln. In: *Tagungsband der 30. Deutsche Arbeitsbesprechung über Fragen der Unkrautbiologie und -bekämpfung* (20–24 February, online), pp. 48-54. Braunschweig, Germany: Julius Kühn-Institut.

Bretagnolle, V. & Gaba, S. (2015) Weeds for bees? A review. *Agronomy for Sustainable Development*, 35, 891–909.

Christin, S., Hervet, É. & Lecomte, N. (2019) Applications for deep learning in ecology. *Methods in Ecology and Evolution*, 10(10), 1632–1644.

Font, X. (2016). *Banc de Dades de Biodiversitat de Catalunya*. http://biodiver.bio.ub.es/biocat/homepage.html

Fried, G., Kazakou, E. & Gaba, S. (2012) Trajectories of weed communities explained by traits associated with species' response to management practices. *Agriculture, Ecosystems & Environment*, 158, 147–155.

Gaba, S., Perronne, R., Fried, G., Gardarin, A., Bretagnolle, F., Biju-Duval, L. et al. (2017) Response and effect traits of arable weeds in agro-ecosystems: a review of current knowledge. *Weed Research*, 57(3), 123–147.

Gerhards, R., Andújar Sanchez, D., Hamouz, P., Peteinatos, G.G., Christensen, S. & Fernandez-Quintanilla, C. (2022) Advances in site-specific weed management in agriculture—A review. *Weed Research*, 62(2), 123–133.

Gerhards, R. & Oebel, H. (2006) Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. *Weed Research*, 46(3), 185–193.

Gerowitt, B. & Heitefuß, R. (1990) Weed economic thresholds in the Federal Republic Germany. *Crop Protection*, 9(5), 323–331.

Gunton, R.M., Petit, S. & Gaba, S. (2011) Functional traits relating arable weed communities to crop characteristics. *Journal of Vegetation Science*, 22(3), 541–550.

Gutjahr, C., Sökefeld, M. & Gerhards, R. (2012) Evaluation of two patch spraying systems in winter wheat and maize. *Weed Research*, 52(6), 510–519.

Hasan, A.S.M.M., Diepeveen, D., Laga, H., Jones, M.G.K. & Sohel, F. (2023) Object-level benchmark for deep learning-based detection and classification of weed species. *Crop Protection*, 177, 106561.

Hasan, A.S.M.M., Sohel, F., Diepeveen, D., Laga, H. & Jones, M.G.K. (2021) A survey of deep learning techniques for weed detection from images. *Computer and Electronics in Agriculture*, 184(3), 106067.

Jørnsgård, B., Rasmussen, K., Hill, J. & Christiansen, J.L. (1996) Influence of nitrogen on competition between cereals and their natural weed populations. *Weed Research*, 36(6), 461–470.

Leutner, B., Horning, N., Schwalb-Willmann, J. & Hijmans, R.J. (2022) *Tools for remote sensing data analysis: RStoolbox*. https://github.com/bleutner/RStoolbox

LfL Bayern. (2024). *Leitunkräuter im Getreide*. https://www.lfl.bayern.de/ips/unkraut/131212/index.php

Marshall, E.J.P., Brown, V.K., Boatman, N.D., Lutman, P.J.W., Squire, G.R. & Ward, L.K. (2003) The role of weeds in supporting biological diversity within crop fields. *Weed Research*, 43(2), 77–89.

Maskell, L.C., Henrys, P., Pescott, O.L. & Smart, S.M. (2020) Long-term trends in the distribution, abundance and impact of native 'injurious' weeds. *Applied Vegetation Science*, 23(4), 635–647.

Neve, P., Barney, J.N., Buckley, Y., Cousens, R.D., Graham, S., Jordan, N.R. et al. (2018) Reviewing research priorities in weed ecology, evolution and management: a horizon scan. *Weed Research*, 58(4), 250–258.

Oerke, E.-C. (2006) Crop losses to pests. *The Journal of Agricultural Science*, 144(1), 31–43.

Pakeman, R.J., Karley, A.J., Newton, A.C., Morcillo, L., Brooker, R.W. & Schöb, C. (2015) A trait-based approach to crop–weed interactions. *European Journal of Agronomy*, 70, 22–32.

Perronne, R., Gaba, S., Cadet, E. & Le Corre, V. (2014) The interspecific and intraspecific variation of functional traits in weeds: diversified ecological strategies within arable fields. *Acta Botanica Gallica*, 161(3), 243–252.

R Core Team. (2021) *R: A language and environment for statistical computing*. https://www.r-project.org/

Rai, N., Zhang, Y., Ram, B.G., Schumacher, L., Yellavajjala, R.K., Bajwa, S. et al. (2023) Applications of deep learning in precision weed

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management: A review. *Computers and Electronics in Agriculture*, 206(7), 107698.

Ruiz-Colmenero, M., Bienes, R., Eldridge, D.J. & Marques, M.J. (2013) Vegetation cover reduces erosion and enhances soil organic carbon in a vineyard in the central Spain. *CATENA*, 104, 153–160.

Sapkota, R., Stenger, J., Ostlie, M. & Floures, P. (2023) Towards reducing chemical usage for weed control in agriculture using UAS imagery analysis and computer vision techniques. *Scientific Reports*, 13, 6548.

Storkey, J. (2006) A functional group approach to the management of UK arable weeds to support biological diversity. *Weed Research*, 46(6), 513–522.

Storkey, J., Meyer, S., Still, K.S. & Leuschner, C. (2012) The impact of agricultural intensification and land-use change on the European arable flora. *Proceedings of the Royal Society B: Biological Sciences*, 279(1732), 1421–1429.

Storkey, J. & Westbury, D.B. (2007) Managing arable weeds for biodiversity. *Pest Management Science*, 63(6), 517–523.

The Royal Society of London. (2009) *Reaping the benefits: science and the sustainable intensification of global agriculture*. London: The Royal Society.

Timmermann, C., Gerhards, R. & Kühbauch, W. (2003) The economic impact of site-specific weed control. *Precision Agriculture*, 4, 249–260.

Veeranampalayam Sivakumar, A.N., Li, J., Scott, S., Psota, E., Jhala, A.J., Luck, J.D. et al. (2020) Comparison of object detection and patch-based classification deep learning models on mid- to late-season weed detection in UAV imagery. *Remote Sensing*, 12(13), 2136.

Wäldchen, J. & Mäder, P. (2018) Machine learning for image based species identification. *Methods in Ecology and Evolution*, 9(11), 2216–2225.

Wu, Z., Chen, Y., Zhao, B., Kang, X. & Ding, Y. (2021) Review of weed detection methods based on computer vision. *Sensors*, 21(11), 3647.

Zingsheim, M.L. & Döring, T.F. (2024) What weeding robots need to know about ecology. *Agriculture, Ecosystems & Environment*, 364, 108861.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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