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Spatial and temporal aspects of weeds distribution within agricultural fields – A review

Lior Blank [a,*], Gal Rozenberg [a,b], Roni Gafni [c,d]

[a] Department of Plant Pathology and Weed Research, Agricultural Research Organization (ARO), Volcani Center, Rishon LeZion, Israel
[b] Faculty of Civil and Environmental Engineering, Technion-Israel Institute of Technology, Israel
[c] The Robert H. Smith Institute of Plant Sciences and Genetics in Agriculture, The Hebrew University of Jerusalem, Rehovot, Israel
[d] Department of Plant Pathology and Weed Research, ARO, Newe Ya'ar Research Center, Ramat Yishay, Israel

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ABSTRACT

Understanding how weeds spread in fields has been a central theme in the agricultural literature for the past three decades, including topics such as weed management and weed community assembly. This understanding is pivotal for optimizing herbicide use. Here, we present the results of a literature review focusing on the spatial and temporal distribution of weeds within fields over the last three decades. Eighty-one articles that met the inclusion criteria were included in the final analysis. These papers studied the distribution of 141 species. We found that 86% of the species studied had patchy distribution. Nevertheless, almost half of the studies focused on only one field, and 63% covered one to two years, which is insufficient to study the dynamics of weed distribution over time. In addition, 97% of the studies were on crop fields, while orchards and vineyards were only rarely studied. This review emphasizes the need for more long-term studies to better understand the temporal dynamics of weed patches during and between growing seasons, and examine the factors that might affect them.

1. Introduction

Weeds cause the highest potential yield loss (34%), followed by pests and pathogens (18% and 16%, respectively) (Oerke, 2006). Global economic losses resulting from weeds have been estimated at more than 100 billion USD per annum (Appleby et al., 2000), despite worldwide herbicide sales of 25 billion USD per year (Swanton et al., 2015). Herbicides account for 47.5% of the total pesticides used (De et al., 2014). Nevertheless, weeds problems are increasing due to the emergence of herbicide resistance (Heap, 2021). In addition, herbicides can cause adverse effects on biodiversity (Freemark and Boutin, 1995), human health (Jepson et al., 2014; Wilson and Tisdell, 2001), and underground water (Pretty et al., 2000). However, herbicides are still crucial to maintaining high yields; Kudsk and Streibig (2003) and Hicks et al. (2018) noted that research is needed to optimize their use.

A site-specific weed management approach (SSWM) was proposed to address these issues (Esposito et al., 2021). Herbicides are typically sprayed uniformly over a field, regardless of weed density and spatial distribution, which results in over-spraying in weed-free areas. The basis for this approach lies in the growing understanding that the distribution of weeds in crop fields is heterogeneous. To implement SSWM farmers need accurate maps of weed-infested areas in their fields (Ribeiro et al., 2005). Generating weed maps can be accomplished by scouting the field, using remote sensing e.g., satellites, airplanes, and drones, or using proximal sensing, i.e., sensors and cameras mounted on tractors, towers, and the like (Herrmann and Berger, 2021). Implementing SSWM approach can effectively reduce herbicide use by 40%–60% (Jensen et al., 2012), thereby reducing the environmental impact and farm costs. Despite extensive research on SSWM over the past three decades, the adoption of precision farming practices such as SSWM has been slow (Fernández-Quintanilla et al., 2018; Lamb et al., 2008; Lati et al., 2021). As agricultural systems exhibit spatial and temporal heterogeneity and various weed species vary in dispersal, phenology, and life form, it remains uncertain whether the SSWM approach would be applicable and effective if developed based on particular assumptions, such as geographical locations, cropping systems, or timing during the growing season. A better understanding of the spatiotemporal dynamics of weed distribution should address these issues and thus facilitate the adoption of the SSWM approach.

* Corresponding author.
E-mail address: liorb@volcani.agri.gov.il (L. Blank).

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1.1. Spatial patterns of weeds

The study of species distribution in an agricultural system is particularly challenging due to the agro-ecosystem's heterogeneous and complex nature (Karp et al., 2018; Krasnov et al., 2021). A wide range of variability exists at the regional scale due to numerous factors, including climate; management activities in neighboring fields; agricultural landscapes (e.g., crop rotation, uprooted plots); and soil composition (Ben-Hamo et al., 2020; Cohen et al., 2017; Firester et al., 2018; Gafni et al., 2023; Krasnov et al., 2019; Sciarretta and Trematerra, 2014; Tsror et al., 2020). Variations at the local scale affecting pest distribution include growers' experience, cultural practices, soil characteristics (e.g., depth, moisture), microclimates and topography (Bagavathiannan et al., 2019; Blank et al., 2016, 2022; Krasnov et al., 2019). The conditions exerted by different management practices of different types of crops have been shown to shape weed communities according to the species' functional traits (e.g., seed weight, plant height) and phenological traits (Fried et al., 2008; Gunton et al., 2011; Hallgren et al., 1999; Smith et al., 2008).

Many studies have shown that different weed species in different crop systems tend to spatially cluster (Colbach et al., 2000; Heijting et al., 2007a; Rozenberg et al., 2021; San Martín et al., 2015). Dispersal processes are primarily responsible for the spatial pattern of seeds in the soil, in addition to local management practices e.g., cropping history, tillage system, herbicide application, and more (Heijting et al., 2007a). However, few studies have examined the impact of such factors on weed distribution.

1.2. Temporal pattern of weeds

To better understand the temporal dynamics of weed distribution, it is also necessary to collect data for a certain field over the course of several years. The spatial stability of weed patches has been shown by several studies (Blanco-Moreno et al., 2004; Blank et al., 2019; Heijting et al., 2007b; Wilson and Brain, 1991). However, some studies have shown temporal inconsistency in weed distribution. According to Johnson et al. (1996), the edges of patches change considerably from season to season. In their four years study, Gerhards et al. (1997) concluded that the spatial pattern of *Setaria pumila* and *Setaria viridis* was unstable. Therefore, generalizing weed patch temporal stability is problematic.

1.3. Crop system

Crop types and their management affect the weed species composition that emerged in the field (Fried et al., 2008), which might affect weed spatial distribution observed in the field. Different crops have different canopy structures (Colbach et al., 2019), which can create different microclimates within the field. For example, a dense, tall canopy crop, such as maize, may create a less favorable microclimate for weed growth, resulting in fewer weeds growing under the canopy compared to a crop with a more open canopy, like soybeans (Van Heemst, 1985). A more competitive crop can suppress weed growth more effectively, leading to a lower density of weeds in the field (Aharon et al., 2021). In contrast, onion is considered a weak competitor with weeds due to its slow growth rate, shallow root depth, and foliage structure (Khokhar et al., 2006). Mechanized practices may also play an important part in weed seed distribution. For example, the increase in weed seed dispersal in crop systems is often attributed to the use of combine harvesters resulting in weed patches elongated in the direction of the rows (Colbach et al., 2000). In that sense, cropping systems might be relevant when studying the spatial distribution of weeds.

1.4. Mapping methods

One method that can be used to implement SSWM is to create an accurate map of weed-infested areas in the field (Ribeiro et al., 2005). Weed maps can be generated by scouting the field. Another method of mapping weeds can utilize data from relatively recent technological advances in remote and proximal sensing. Indeed, in the last decade, airborne e.g., satellite, airplane, and UAV, and proximal sensing have become a major platform for mapping weeds and studying the spatial aspects of weed distribution.

This work reviewed the literature focusing on the spatial distribution of weeds within agricultural fields over the last three decades. We used an extensive survey to characterize various weed distribution research aspects to identify research gaps. Specifically, we looked for possible changes in four aspects of weed distribution over the last 30 years, and asked four principal questions: (1) How common has aggregated spatial distribution been among studied species? (2) How central was the temporal aspect in studying weed distribution? (3) Does the literature on weed distribution within fields represent all crop types? (4) Have weed mapping methods changed during the last three decades?

2. Methods

2.1. Literature survey

We systematically searched relevant literature using the ISI Web of Science (WoS). The following search criteria were used in December 2019: TOPIC: (weed*) AND TOPIC: (spatial OR temporal OR distribution OR pattern AND analy*) AND TOPIC: (patch* OR aggregat* OR Random OR Uniform* OR Homogeneous OR Heterogeneous). No geographical restrictions were applied during the screening process, and the search period in ISI WoS was 1984–2019. We found a total of 463 articles in this search. An additional three records came from the authors' collections of relevant literature. To ensure the inclusion of only relevant and original research, we only included English-language papers that were not review papers in our analysis. The shortlist of papers analyzed in this review did not include papers that produced weed maps without examining their spatial and temporal distribution. In addition, to avoid duplication of reports, articles referencing data collected in earlier studies were discarded. The articles were screened using several criteria: (a) peer-reviewed articles (as opposed to book chapters or conference abstracts), (b) articles that quantified or estimated weed distribution in the plots studied, and (c) studies that took place in an agricultural setting (e.g., and not in pastures or natural areas). This produced 81 full-text articles, which were further screened. The complete list of publications utilized is listed in Appendix S1. Fig. 1 shows the geographical locations of the studies included in our dataset.

2.2. Article characterization

Information about the research in the 81 articles was extracted, including (i) Crop type; (ii) Crop system, i.e., Crop/Orchard/Vineyards; (iii) Weed species' name (iv) Spatial pattern of each studied species, i.e., aggregate/random/varies (which was not conclusive in the study and varied between fields, seasons or the geostatistical method used); (v) Number of fields included in each study, and (vi) Length of the study in years; (vii) Weed mapping method, i.e., Scouting/Satellite/Airplane/UAV/Proximal (tractor/tower/camera etc.)

A $\chi 2$ test was used to determine levels of significance between crop systems and species ($P < 0.05$).

3. Results and discussion

In order to generalize across species and systems, to better understand weed patch spatiotemporal dynamics, and to make appropriate management decisions, we need to better understand the fundamental link between spatial distribution and temporal dynamics and the factors shaping these patterns. Increasing the knowledge of these dynamics and factors will aid in optimizing herbicide application spatially (where to

Fig. 1. Map showing the distribution of reviewed papers by country.

spray), temporarily (when to spray), and the amount of herbicides needed, thus reducing adverse effects on the environment and farmer's costs.

3.1. Selection of articles

The papers selected studied the distribution of 141 species. Studies on the spatial distribution of weeds focusing on annuals comprised 74% of the species studied. The most studied species were *Chenopodium album* (appearing in 19 studies), *Abutilon theophrasti,* and *Galium aparine* (10 studies each). The distribution of weed communities was also examined in 12 studies. While we cannot infer the climate conditions and ecosystems from such a survey, we conservatively estimate that most of the research on weed distribution was done in temperate and Mediterranean regions (Fig. 1). Few studies have been performed in dry or tropical ecosystems. Thus, a better representation of these and other ecosystems is needed. This will help determine if the spatiotemporal dynamics of weeds found in this review are a general phenomenon.

3.2. Spatial patterns of weeds

Many studies have shown that different weed species tend to spatially cluster (Table S1). These studies found that herbicides are typically applied uniformly throughout the field, resulting in excess herbicide use. For example, when Rozenberg et al. (2021) used a UAV (Unmanned Aerial Vehicle) to map weeds in onion fields, they found that weeds covered less than 7% of the field in five out of 11 fields. Nevertheless, herbicides were applied over the entire area of all 11 fields. Considering weed distribution could significantly reduce herbicide use. Another study that supports the need to account for the spatial pattern of weeds is Castaldi et al. (2017), which compared uniform herbicide application to patch spraying according to an application map. They concluded that the latter could save up to 40% of the herbicides used in a uniform application. This herbicide reduction would save 16 to 45 € per ha without adversely affecting crop yield. Hamouz et al. (2013) reported that SSWM in winter wheat can reduce herbicide usage by 15–100% without compromising yields.

In support of advancing to more precise weed management, we found in our literature survey that 86% of the species had patchy distribution. Furthermore, the spatial distribution of six species groups: *Amaranthus* spp. (four studies), *Setaria* spp. (four studies), *Avena* spp., *Cruciferous* spp., *Solanum* spp., and *Veronica* spp. (one study for each species), was evaluated and found to be aggregated, except for one study that found *Setaria* spp. to be randomly distributed (Table S1). Ten papers evaluated the spatial distribution of the entire weed communities present in the fields studied, and found them to be aggregated. With regards to single weed species, aggregation was the predominant spatial pattern for *Abutilon theophrasti* ($p = 0.02$ by $\chi 2$ test), *Chenopodium album* ($p = 0.0003$), and *Galium aparine* ($p = 0.002$).

Dispersal processes are primarily responsible for the spatial pattern of seeds in the soil (Wiles and Brodahl, 2004). Most weed seeds cluster around the mother plant. With *Ecballium elaterium*, which distributes only by seeds, the patchy distribution may be the result of a unique seed dispersion mechanism that does not rely on wind or water support, so most of the seeds are established near the mother plant, resulting in an aggregated pattern of plants (Blank et al., 2019). However, the number of seeds that land on a particular area depends on various factors, including the height and density of the seed source, the size and shape of the seeds, wind speed and direction, and the spatial heterogeneity of parent plants (Bertiller, 1998; Harper, 1977; Howe and Smallwood, 1982). Shaukat and Siddiqui (2004) compared seed banks and above-ground vegetation samples, and found that seed banks and above-ground vegetation were qualitatively similar. Granivory may also affect the distribution of seeds in the soil (Price and Reichman, 1987). Similarly, plants that propagate via tubers that grow from underground rhizomes in the vicinity of the mother plant result in a patchy distribution e.g., *Sorghum halepense* (Andújar et al., 2012; San Martín et al., 2015). The patchy pattern observed also results from heterogeneous environmental conditions e.g., soil spatial heterogeneity, microclimate conditions, shade, etc. (Metcalfe et al., 2018; Walter et al., 2002), competition between species, or a combination of these factors (Cardina et al., 1997; Thill and Mallory-Smith, 1997).

A patchy distribution can also result from weed seeds or propagules dispersed by wind or other vectors. For example, a random distribution pattern can be expected for wind-borne seeds, such as dandelion (Goudy et al., 2001; Heijting et al., 2007a) and *Sonchus asper* (Heijting et al., 2007a). However, Goudy et al. (2001) suggested that the timing of seed production might affect weed distribution. For example, some species, such as *Taraxacum officinale*, spread their seed relatively early in the season, thus avoiding the crop canopy closure, allowing free movement of seeds throughout the field. Late-maturing species, like *Sonchus asper*, might be restricted by the crop canopy, resulting in seed shedding in proximity to the parent plant (Goudy et al., 2001). This highlights the importance of studying weed distribution within a season.

We found that weed distribution is frequently examined in a restricted number of fields. About 46% of the articles studied only one field, and only 22% of the studies encompassed more than five fields (Fig. 2). The small sample size poses challenges in making meaningful generalizations and limits the ability to account for significant local variations, such as diverse management practices used by farmers in different ways (Freckleton et al., 2018), and regional variability, such as differences in climate and topography between agricultural fields (Gafni et al., 2023). More work is needed to better understand which species tend to aggregate and form stable patches in response to management practices (e.g., crop rotation or weed control intensity) or field characteristics (edaphic conditions, geographic location, shape, etc.). In fact, eight species had contrasting distributions in different studies e.g., *Avena fatua* was found to be random by Dessaint et al. (1991) but

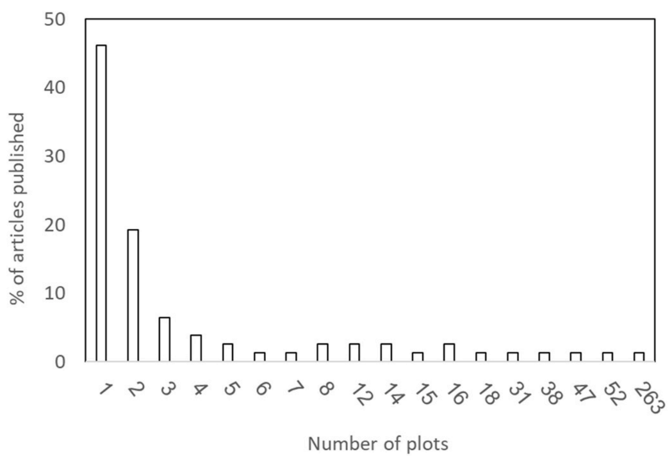

Fig. 2. The distribution of publications based on the number of plots.

aggregated by Gerhards and Oebel (2006). Similarly, Goudy et al. (2001) and Heijting et al. (2007a) found the distribution of *Taraxacum officinale Weber* to be random, Mulugeta and Stoltenberg (1997a, 1997b) found it to be aggregated. Wyse-Pester et al. (2002) proposed that the lack of spatial dependence for some of the species in their survey might result from inadequate sampling unit size and placement or human error in measuring. This means that seed dispersal and germination could occur below the observed separation distances between sample units. Accordingly, Weisz et al. (1995) determined that sampling unit size could contribute to finding pure nugget effects, indicating the absence of spatial dependence. Sample size (Hamouz et al., 2006) and quadrat size (Dille et al., 2002) were found to be critical for accurately mapping weeds.

Another explanation might involve seed density. According to Dessaint et al. (1991), the spatial pattern of seeds was primarily determined by seed density, with abundant species having aggregated patterns. In line with this, Shaukat et al. (2004) found that of the 27 species recorded in the seed bank, 21 showed an aggregated pattern. They concluded that species with low seed density exhibited Poisson distribution, while species with moderate to high seed density exhibited aggregated patterns.

Lastly, differences in local management actions, such as cropping history, tillage system, and herbicide application, might also explain the spatial distribution of weeds. The aggregated pattern tends to be more common in no-till fields than in plowed fields. Cardina et al. (1996) suggested that when seeds are mixed during tillage, they are likely to be less aggregated, more random, and therefore less spatially dependent. Furthermore, seeds are buried and diluted in the soil during tillage, making patchiness less noticeable. Barroso et al. (2012) found that combined harvesting disperses *S. halepens* seeds and may lead to a less aggregated distribution of this species. Heijting et al. (2007a) studied the dispersal of weed seeds in fields during harvest, using a range of plant species as model weeds. The authors concluded that the rigid-tine cultivator is likely contributing to dispersal in the direction the cultivator is driven by dragging plant material with seeds through the field. A study conducted by Cohen et al. (2017) found that *Phelipanche aegyptiaca* seeds are blown from an infested field to a distance of 90 m, leading to infestations in neighboring fields and possibly accounting for the high infestation near the borders of the fields. Furthermore, organic farming can also lead to different aggregation patterns than conventional no-tillage systems (Pollnac et al., 2008). The latter showed high weed density patches mixed with weed-free gaps, while organic systems showed patchiness at multiple scales with few gaps, suggesting that the various processes, which produce aggregation, are different.

3.3. *Temporal pattern of weeds*

Contrary to the relatively well-studied spatial aspects of weeds in agricultural fields, the temporal aspects, which require data collection in subsequent years or multiple times during a growing season, have received less attention. In our literature survey, we found that 63% of studies cover a period of one to two years, which is insufficient for studying the temporal dynamics of weed distribution (Fig. 3). Only 6% of the studies exceeded five years. In several studies on weed patches, the spatial aspects of the patches appear to be relatively stable over time (Blanco-Moreno et al., 2004; Blank et al., 2019; Heijting et al., 2007b; Wilson and Brain, 1991). Heiting et al. (2007b) attributed instability to the species' dispersion mechanism, which is greater for wind-dispersed seeds and for species with sparser populations. Other field studies showed that pre-harvest dispersal was important for patch stability of annual weed species since it results in compact and dense seed patches (Gerhards et al., 1997; Wilson and Brain, 1991).

Understanding the temporal dynamics of weed distribution can help improve weed management making it more effective and precise (Gerhards et al., 2022; Lati et al., 2022). For example, pre-emergence herbicides can be applied early in the growing season, based on the dynamics of patches, even before visual signs of infestation are apparent (Lati et al., 2022). In this regard, the spatial distribution of weeds from one year could serve as a basis for making management decisions the following year (Koller and Lanini, 2005; Lati et al., 2022), given a reasonable degree of patch stability. The stability of weed patches provides another advantage to pre-emergence treatments: farmers can estimate the quantity of herbicides needed in advance, thus optimizing the purchase and reducing costs. In addition, the timing of herbicide applications can be improved by better understanding weed populations' temporal dynamics. For example, if post-emergence management is applied too early, i.e., before most weeds have emerged, it may result in low returns and lead to ecological consequences such as herbicide off-target effects, as well as agro-management costs such as soil compaction.

Relatively short-term studies appear to be common in many ecological and agricultural studies because collecting data in such systems is a resource-intensive and time-consuming process. According to meta-analyses on crop pollination (Lowe et al., 2021), plant storage dynamics (Martínez-Vilalta et al., 2016), and bird distribution (Bayard and Elphick, 2010), the average study duration was 2.3, 1.2, and 2.5 years, respectively. Thus, generalizing from previous findings on patch stability is limited when previous studies looked at very few fields over a relatively short time span.

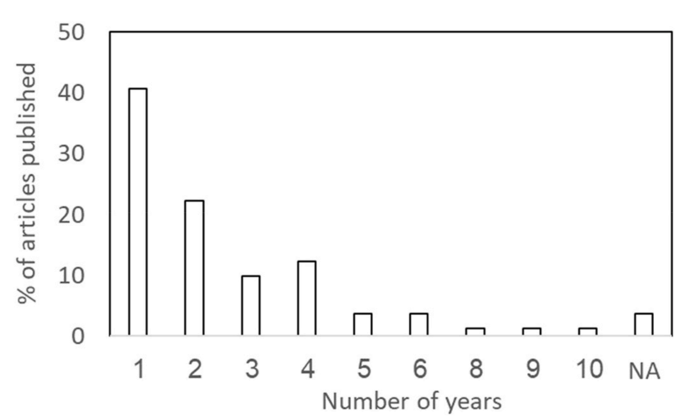

Fig. 3. The distribution of publications according to the duration of the studies, measured in years.

3.4. Crop system

In our literature survey, most of the research that studied weed distribution was in crop fields (97% of the studies) and not in orchards (1.5%) or vineyards (1.5%). The crops most studied were corn (27%) and wheat (23%) (Fig. 4). Weed aggregation was the predominant spatial pattern in the four common crops (maize, wheat, soybean and barley) ($p < 0.0001$; χ^2 test). Various crops have different competitive characteristics, including rapid germination and root development, early vegetative growth and vigor, rapid canopy closure, high leaf area expansion rate, greater height, and profuse tillering or branching (Lemerle et al., 1996). For instance, wheat exhibits rapid germination and root development, along with rapid leaf area expansion and a high tillering capacity, enabling it to compete effectively against weeds. On the other hand, crops like chickpea (Nasrolahzadeh et al., 2012), onion (Khokhar et al., 2006), and tef (Tefera, 2002) are considered poor competitors with weeds. Such differences between crops can affect weed species composition. For example, Hakansson (1983) found that high crop density selects for weeds that can climb, such as *Polygonum convolvulus* and *Galium aparine*, while rosette weeds population, such as *Brassica napus* and *S. asper*, declined. Additionally, crops differ in their cultural practices, such as herbicides and tillage, fertilization, time of tillage and harvest date in relation to weed and crop emergence (Ball and Miller, 1990; Slife, 1976). Over the course of the growing season, these agronomic practices can affect the composition of weed species. Thus, when farmers rotate their crops, they change the conditions in their fields and therefore change the observed dynamics of weed patches.

Weed species characterized by an unstable patchy distribution will naturally require higher mapping frequency compared with spatial stable weed species. This understanding is particularly pertinent to orchards because the use of remote sensing e.g., satellites, airplanes, or UAVs in orchards is limited. Remote sensing can only be used to map weeds between rows and cannot accurately detect weeds under the canopy. Due to this constraint, the issue of temporal consistency in patch locations in orchards might be even more important than in crop systems.

3.5. Mapping methods

According to our findings, scouting was the most frequently used method for mapping weeds, with approximately 78% of the studies employing this technique (Fig. 5). However, scouting is known to be a time-consuming and costly task (Schuster et al., 2007), which often necessitates additional interpolation for estimating weed infestation in unsampled areas (Rew and Cousens, 2001). Furthermore, scouting for weeds on a commercial scale is often unfeasible, especially when aiming to properly represent the intra-field infestation state (Freckleton et al., 2018; Rew and Cousens, 2001). Numerous studies used UAVs to map weeds (Mohidem et al., 2021, Rozenberg et al., 2021); however, we found that only 5% of the studies used UAVs to study the spatial distribution or temporal dynamics of weeds. UAV platforms used in weed mapping have several advantages, primarily the ability to fly at low altitudes, enabling greater spatial resolution imagery, and the possibility of identifying small individual plants or small weed patches, and mapping specific weed species (Rozenberg et al., 2023; Xiang and Tian, 2011). Nonetheless, despite their high spatial resolution, species identification and simple automated classification procedures remain a challenge (Mohidem et al., 2021). Furthermore, UAVs suffer from some limitations, such as the inability to fly on windy and rainy days, which might produce blurry images. Other factors can also limit the use of UAVs, including safety concerns that require coordination with air traffic control agencies, security considerations such as avoiding airports and international borders, and regulatory requirements such as the need for insurance to address civil liability issues associated with flights (Carr, 2013).

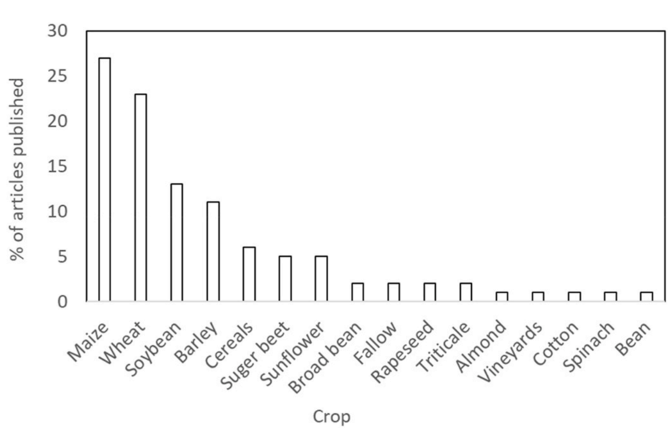

Fig. 4. The distribution of published articles based on the studied crops.

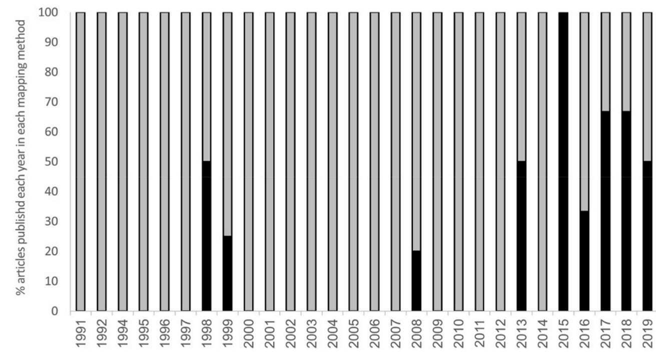

Fig. 5. The shift over time in the use of scouting (shown in gray), remote sensing (including UAVs, satellites, and airplanes) and proximal sensing (represented in black) as methods for weed mapping.

Recent advances in robotic and computer vision (proximal sensing) have led to the development of robotic weeders that can detect weeds and remove them mechanically or precision spray in real-time without requiring preview maps (Machleb et al., 2020; Merfield, 2023). Nevertheless, proximal sensing was used in only a small number of studies we reviewed (Fig. 5). Satellite images have been widely used for land cover classification (Phiri and Morgenroth, 2017), determining crop health (Mutanga et al., 2017), yield prediction (Lobell et al., 2015), and to a lesser extent, for mapping invasive plants (Royimani et al., 2019).

Additional developments in satellite technology enable us to observe the earth at unprecedented spatial (30–50 cm), spectral, temporal (daily/weekly revisit time), and resolution using satellite sensors such as Pléiades-1A (50 cm), Pléiades Neo (30 cm), SkySat (57 cm), and WorldView-4 (31 cm) (Zhang et al., 2020). However, almost all previous studies on invasive weeds have been carried out in natural areas (Everitt et al., 2005; Li et al., 2020). Using satellite imagery to map weeds is subject to some limitations. Perhaps the relative coarse resolution of satellite images makes them less suitable for mapping weeds (Rasmussen et al., 2021). In addition, the primary disadvantage of satellite imagery is its dependency on a clear, cloud-free view of the sky. Another disadvantage of satellite imagery is the need for significant levels of data processing.

Nonetheless, remote sensing via satellites may facilitate our understanding of weeds' spatial patterns. De Castro et al. (2013) utilized satellite imagery to map *cruciferous* spp. patches in winter wheat in over 260 fields. Such an extremely high number of fields examined, especially when compared to most studies, combined with the ability to use imagery archives, and frequency of satellite image acquisition, may be used to study spatiotemporal dynamics of weeds. In our literature survey, about 3% of the studies used satellite images to map weeds. However, in recent years, weed mapping has shifted from scouting to remote sensing (Fig. 5).

4. Conclusions

Studying the spatiotemporal distribution of weeds addresses a pressing environmental and agricultural concern: the need to reduce herbicides used for weed management. Herbicides are an essential tool for weed control; nevertheless, their use can cause adverse effects on the environment. Given the widespread phenomena of herbicide resistance, the ongoing climate change, and the increasing trend in global trade facilitating long-distance weed dispersal, weed problems will likely worsen in the future (Ramesh et al., 2017; Shabani et al., 2020). This review highlights the importance of conducting long-term studies in diverse ecosystems and conditions to gain a better understanding of the temporal dynamics of weed patches during and between growing seasons, as well as the factors that might affect them. In addition, long-term studies would allow the assessment of the effectiveness of the SSWM approach as well as other weed management strategies, such as cover crops and mixed-cropping systems, in controlling weeds. Further research is needed in orchards, where remote sensing technologies are restricted as the canopy obscures the ground, making temporal consistency in weed patch locations important. By finding such temporal dynamics, it may be possible to reduce the frequency of mapping required, compared to orchards where weed distribution is unstable. Lastly, the observed increase in the use of remote sensing for weed mapping in recent years is promising and may enable the development of scalable weed mapping approaches.

Lior Blank: Conceptualization; Data curation; Formal analysis; Methodology; Supervision; Visualization; Roles/Writing - original draft; Writing - review & editing. **Gal Rozenberg**: Conceptualization; Data curation; Methodology; Visualization; Writing - review & editing. **Roni Gafni**: Methodology; Writing - review & editing.

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Data statement

Not applicable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cropro.2023.106300.

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