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Opportunities from Unmanned Aerial Vehicles to Identify Differences in Weed Spatial Distribution between Conventional and Conservation Agriculture

Nebojša Nikolić [1], Pietro Mattivi [2], Salvatore Eugenio Pappalardo [3,*], Cristiano Miele [4], Massimo De Marchi [2] and Roberta Masin [1]

[1] Department of Agronomy, Food, Natural Resources, Animals and Environment—DAFNAE, University of Padua, 35020 Legnaro, Italy; nebojsa.nikolic@unipd.it (N.N.); roberta.masin@unipd.it (R.M.)
[2] Advanced Master in GIScience and UAV for the Integrated Management of Territory and Natural Resources, Department of Civil, Environmental and Architectural Engineering—-ICEA, University of Padua, 35100 Padova, Italy; pietro.mattivi@gmail.com (P.M.); massimo.de-marchi@unipd.it (M.D.M.)
[3] Laboratory GIScience and Drones for Good, Department of Civil, Environmental and Architectural Engineering—ICEA, University of Padua, 35100 Padova, Italy
[4] Archetipo s.r.l., 35129 Padova, Italy; cristiano.miele@archetipo-srl.com
* Correspondence: salvatore.pappalardo@unipd.it

Abstract: Weeds are one of the major issues in agricultural production and they are present in most agricultural systems. Due to the heterogeneity of weed distribution, understanding spatial patterns is paramount for precision farming and improving sustainability in crop management. Nevertheless, limited information is currently available about the differences between conventional agricultural (CV) weed spatial patterns and weed spatial patterns in conservation agricultural systems (CA); moreover, opportunities to use unmanned aerial vehicles (UAV) and recognition algorithms to monitor these differences are still being explored and tested. In this work, the opportunity to use UAVs to detect changes in spatial distribution over time between CA and CV fields was assessed for data acquisition. Acquired data were processed using maximum likelihood classification to discriminate between weeds and surrounding elements; then, a similarity assessment was performed using the 'equal to' function of the raster calculator. The results show important differences in spatial distribution over time between CA and CV fields. In the CA field 56.18% of the area was infested in both years when the field margin effect was included, and 22.53% when this effect was excluded; on the other hand, in the CV field only 11.50% of the area was infested in both years. The results illustrate that there are important differences in the spatial distribution of weeds between CA and CV fields; such differences can be easily detected using UAVs and identification algorithms combined.

Keywords: plant infestation; remote sensing technology; no-till system; UAV; CA; CV

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1. Introduction

Several studies identify weeds as one of the main constraints of plant production in agriculture [1–4]. They are present in every field as remnants of the previous vegetation contained in the soil's seed bank. They can also be imported from other fields or infested areas via natural dissemination propagated by wind, animals, or the plants themselves [5,6]. Seeds or other reproductive organs of different weed species can also be introduced during various agricultural operations such as soil tillage, irrigation, and fertilization [7]. From the time humans started practicing agriculture as a monoculture farming system, weeds have always been the unwanted companions of crop fields [8]. Agricultural systems changed and evolved over time, and weeds always seemed to find a way to adapt, survive, and eventually even thrive in agricultural areas [9,10]. Climate change is currently regarded as one of the most important drivers of weed flora composition modifications as a result of increases in temperature and the level of CO_2 that might promote the proliferation of certain weed species and their competition with crops in different agricultural management systems [11–14]. Two of the most important and very different agricultural systems are conventional (CV) and conservation (CA) agriculture. Conventional agriculture is characterized by the use of different mechanical soil tillage operations [15], while conservation agriculture excludes soil disturbance (no-till systems) or reduces it to a minimum, with incentives to use crop residues and cover crops [16]. These differences in soil management significantly impact the development of weed communities. In CV mechanical operations determine infinite cycles of burying and unearthing seeds present in the seed bank. Therefore, seeds and other reproductive organs can be transported across the field during different tillage operations.

In CA, especially in no-till management CA, there is no soil disturbance, or it is considerably reduced compared to CV. Therefore, the seeds and other reproductive organs remain on the soil surface, usually close to the mother plant [15,17,18].

Since it is known that weeds do not appear uniformly, but rather in patches across a field [19,20], different field management practices might result in changes in weed spatial distribution over time. As weed seeds and other reproductive organs can travel a greater distance due to the different mechanical operations associated with CV, it is expected that CV will display greater changes in weed patch distribution.

On the other hand, in CA where mechanical operations are minimal, seeds usually remain very close to where they originated; therefore, the distribution of weed patches are expected to be more stable over time [21,22].

In addition, differences in soil management can also lead to the formation of different weed communities. In CA there is usually a predominance of annual weeds, opposed to the predominance of perennial weeds in CV, which may contribute to the differences in weed spatial distribution [23].

These differences are important to consider, since as a result of technological improvements, precision farming is becoming more and more important in Europe and the rest of the world [24]. Currently, remote sensing technologies such as unmanned aerial vehicles (UAV) are increasingly used as a tool for weed mapping in agricultural fields in different parts of the world. Many studies were conducted to better understand the possibilities for UAV use in monitoring and detecting weeds in agriculture, with interesting results [25–28]. Given that CA is becoming increasingly adopted globally, as it can reduce labor and fuel costs, as well as time dedicated to cultivation [29], it is paramount to study its specificities and how they influence weed flora. Since its introduction in the 1960s, CA has expanded to 180 million ha worldwide, representing 12.5% of global arable land in 2015/16; the trend seems to be gaining momentum, considering that in 2013/14 the CA area was 157 million ha [30,31]. Even though most of the area under CA is located in South America and in parts of the world struggling with erosion and desertification, the area under CA is also increasing in Europe. In Italy, the area under CA was 283,000 ha, according to the available data [31].

Considering the differences in soil management between CV and CA, there might be a need to implement precision weed control adaptation strategies. To accomplish this, it is important to understand the evolution of weed spatial distribution caused by different field management systems. Therefore, the general aim of the present research is to explore the possibility of using a UAV to acquire high-resolution spatial data and a detection algorithm to track and compare the evolution of weed patches in two experimental plots under CV and CA (no-till) management over two consecutive years. The results should provide a better understanding of changes in weed spatial distribution between CV and CA (no-till) field management systems, leading to the development of better weed control strategies.

2. Materials and Methods

2.1. Study Site

For this study, two different experimental fields were designed; a CV managed field in Pozzoveggiani locality 45°20′38.51″ N 11°54′51.36″ E, and a CA managed field in Legnaro

45°20′49.45″ N 11°57′12.44″ E. Both fields are part of the 'Lucio Toniolo' experimental farm of the University of Padua, and both are located in Legnaro, Padua Province, Veneto Region, Italy (Figure 1).

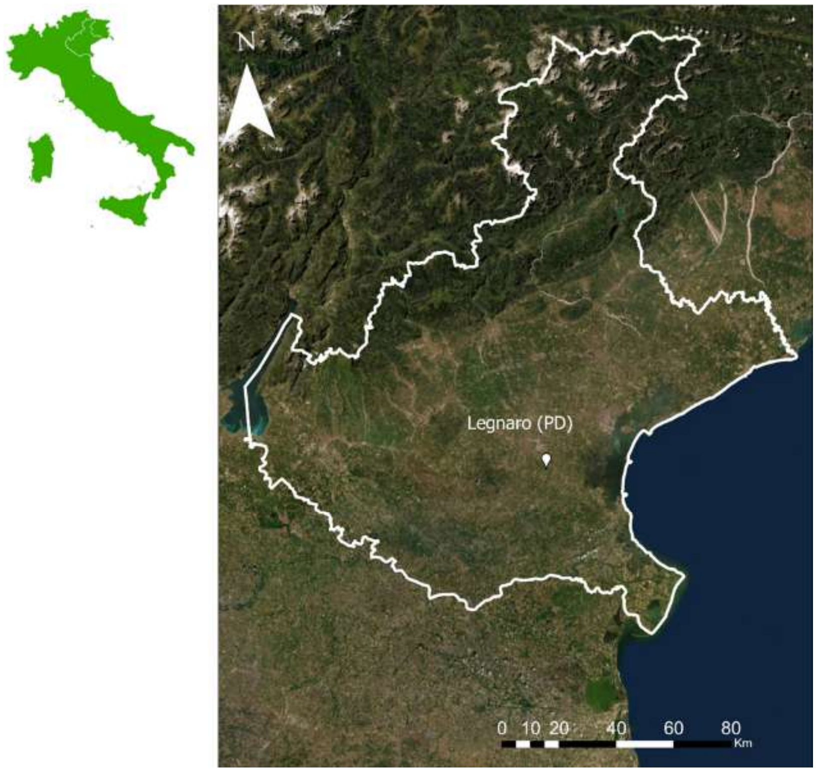

Figure 1. Position of the study sites in the Italian Veneto region.

The surface of both fields is predominantly flat and the soils are classified as Fluvic Cambisols according to the FAO-UNESCO classification, which is common to the Venetian flood plain [32]. The local climate presents sub-humid traits with an average temperature of 12 °C and approximately 800–850 mm/year of rainfall. Precipitation is mostly concentrated in the autumn and spring, based on data from the Regional Agency for Environmental Protection (ARPA); precipitation for the study period and the locality were also provided by the aforementioned agency, and are presented in Figure 2.

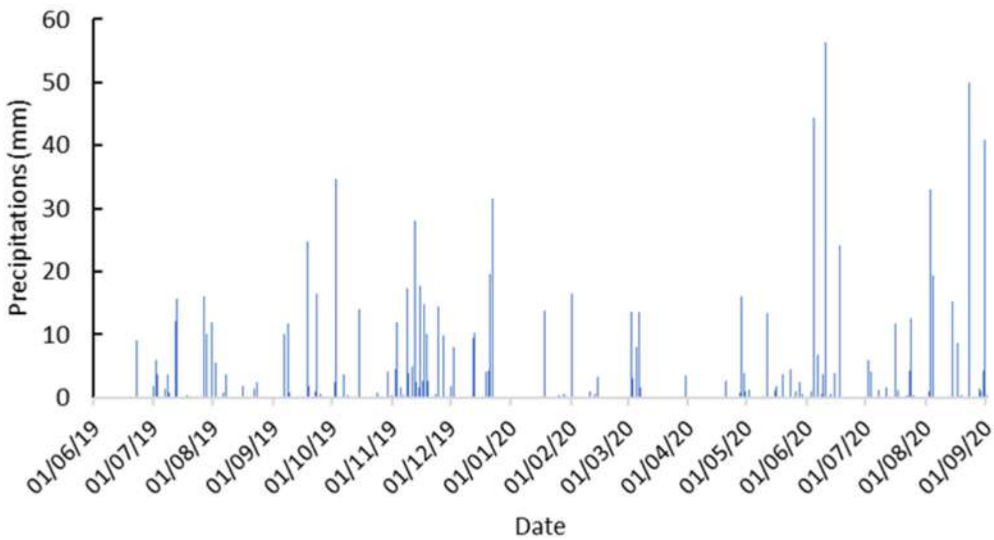

Figure 2. Precipitations during the study period.

At the Pozzoveggiani field, mechanical measures are applied for soil tillage, while the Legnaro field has been managed under no-till practices since 2014. Specifically, the mechanical measures applied in the CV field were as follows: ploughing on 20th September 2018, and harrowing on 5th and 15th of October 2018, before *Lolium multiflorum* was sown. The field was ploughed again on 1st of April 2020 and harrowed on 20th and 24th of April 2020, before soybean was sown. The area of the CV field is 5896.97 m^2, while the area of the CA field is 5643.68 m^2; both fields are represented in Figures 3 and 4, respectively.

Figure 3. The CV in Pozzoveggiani locality, Legnaro (Experimental farm 'Lucio Toniolo', University of Padua, Veneto Region, North).

Figure 4. The CA field at Legnaro (Experimental farm 'Lucio Toniolo', University of Padua, Veneto Region, North).

2.2. UAV Survey

UAV flights were performed twice, in two consecutive years (2019 and 2020), for both fields, for a total of four surveys. The UAV surveys were conducted using a DJI Matrice 200, equipped with DJI X5S sensor (21 M pixel CMOS) (DJI Sciences and Technologies Ltd., Shenzhen, China). The flight plan was set at an altitude of 35 m from the ground; image acquisition during the flight was set at 83% frontal and lateral overlap. For the CA field, the first flight was executed on July 30th 2019 and the second on August 10th 2020, both times after the wheat (*Triticum* sp.) harvest. For the CV field, the first flight was performed on September 12th 2019 after the harvest of Italian ryegrass (*Lolium multiflorum*), and the second on May 29th 2020 before soybean was sown (*Glycine max*). For the creation of the orthomosaics, Pix4D® Mappersoftware (Pix4D S.A., Prilly, Switzerland) was used, providing four different orthophotos at a very high image resolution (2 mm) for further analysis, as can be seen in Figures 3 and 4.

2.3. Weed Classification

For weed classification operations SAGA GIS open-source software (version 7.6.2) was used. The classification was performed using the Maximum Likelihood Classification (MLC) algorithm, part of the supervised classification for grids option of the aforementioned program. The MLC was chosen for its ability to discriminate between weeds and the surrounding elements, as indicated by different authors [33–35]. MLC is based on two principles: that the cells in each class sample in the multidimensional space are normally distributed, and on the Bayes theorem of decision making. Considering these two principles, for each cell corresponding to a single pixel, statistical probability is computed for each class to determine the association of every single cell to a specific class. The MLC represents a classification in which a pixel with the maximum likelihood is classified into the corresponding class [36,37]. The MLC requires a raster file and a sample classification with defined classes as input data, according to which it will produce the maximum likelihood classification [37,38]. Two classes were used for classification: weed and non-weed. As only the weed category was of interest for further analysis, the non-weed category was disregarded. When classification was completed, the newly produced classification was imported into the ArcGIS® Pro program (v2.2.0 Environmental Systems Research Institute (ESRI), Redlands, CA, USA) as a raster file. With the help of the raster calculator function (part of the spatial analyst toolbox that allows the creation and execution of map algebra expressions) it was possible to find the same areas in each field in both years by comparing the two raster files from different years. The 'equal to' function (==) performs a relational 'equal to' operation on two inputs on a cell-by-cell basis, returning 1 for cells where the first raster equals the second raster, and 0 for cells where it does not, as shown in Figure 5 and Equation (1) [39].

$$\text{Equal Raster} = \text{Raster 1} == \text{Raster 2} \tag{1}$$

where Equal Raster contains the pixels that are classified as weeds in both Raster 1 and Raster 2.

Figure 5. Graphical representation of the 'equal to' function between two raster files.

Therefore, if the same pixel was classified as weeds in both years (in two raster files), the result will be 1, while if it was classified as weeds in only one year the result will be

0; the order of the raster files is not important. These values in numeric format can be found in the attribute table of the raster files [39]. After the equal area was determined, it was possible to calculate the percentage of weed distribution difference in the same field comparing two years using a simple Equation (2).

$$x = \frac{a*100}{b} \quad (2)$$

where x represents the percentage of area that was covered with weeds in both years, a is the area that was defined as equal, and b is the total area covered with weeds in the second year.

3. Results

Weed presence differed between the CA and the CV fields; the CA field under no-till management was more infested. Weed presence in the CA field in 2019, 2020, and in both years is shown in Figure 6.

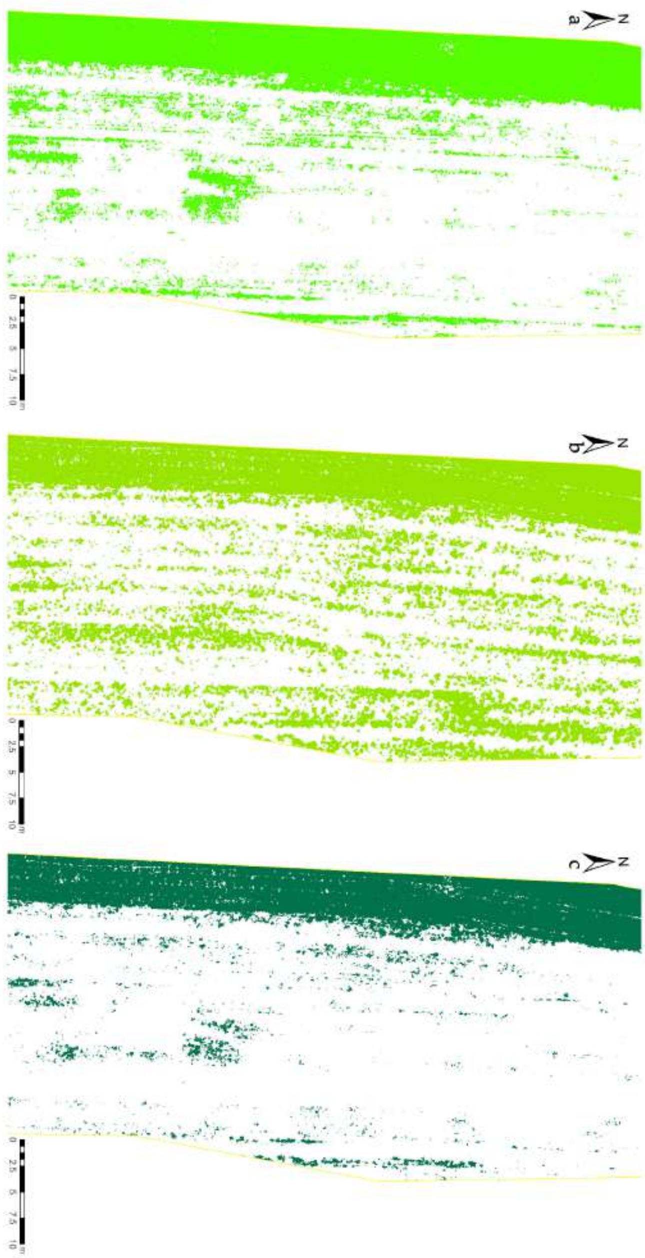

Figure 6. Weed presence in the CA field in 2019 (**a**), 2020 (**b**), and in both years (**c**).

In 2019, the infested area of the CA field, including field margins, was 159 m^2, while in 2020 that area grew to 227.73 m^2. The overlapping area (infested in both years) is equal to 127.94 m^2, which corresponds to 56.18% of the infested area from 2020. Therefore, it seems that in addition to expanding, in 2020 weeds colonized areas that were not infested in 2019, while some areas that were infested in 2019 were weed free in 2020.

In terms of cardinal directions, in 2019 the infestation was mainly concentrated along the western sector, due to the presence of the field margin; other weed areas are localized in the central and southern sector of the parcel (Figure 6a). The northern and eastern sectors of the field were much less infested. In 2020, the infestation appears to remain stable in the previously infested regions; however, it heterogeneously increased in the eastern and northern sectors (Figure 6b).

The infested area of the CV field is represented in Figure 7.

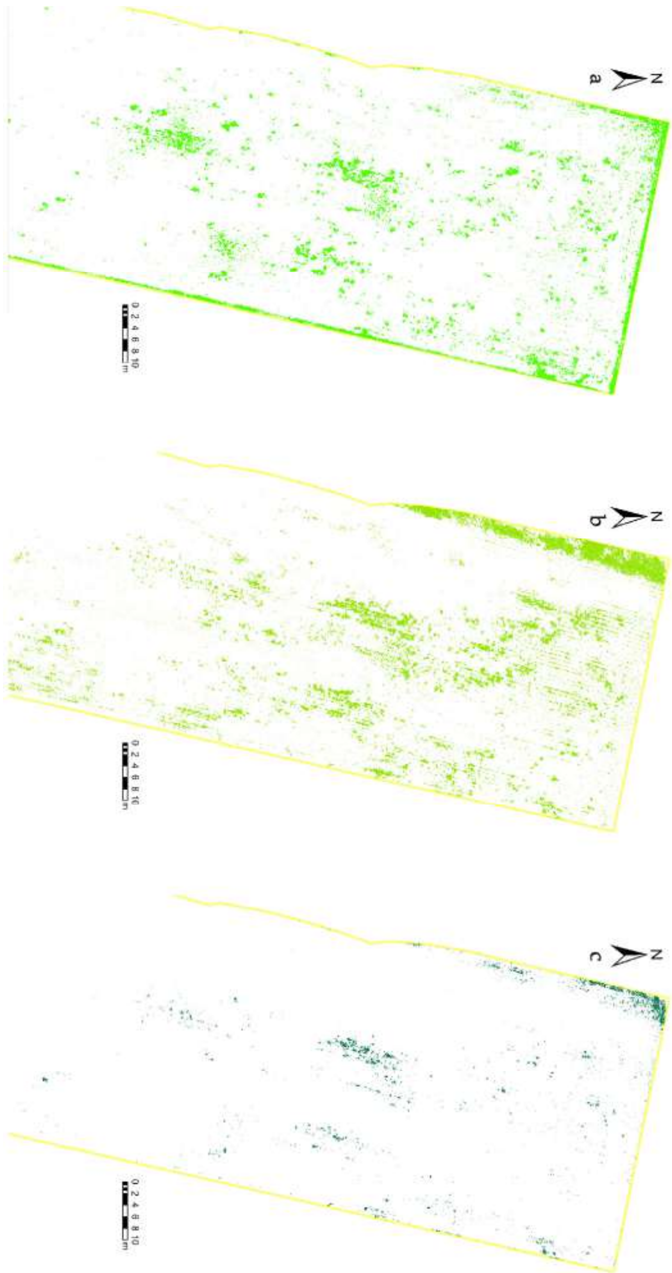

Figure 7. Weed presence in the CV field in 2019 (**a**), 2020 (**b**), and in both years (**c**).

Moreover, an increment of the infested area can also be observed between years, as in the CA field. In 2019, the infested area occupied 63.1 m^2, while in 2020, the area was

77.53 m^2. On the other hand, the area infested in both years was only 8.92 m^2, corresponding to 11.50% of the infested area from 2020. In main cardinal terms the CV field was mostly infested in the northern, central, and eastern sectors, while the southern and western sectors were less infested. In 2020, the infestation shifted more to the south and west of the field, probably as a result of tillage operations.

Therefore, the results indicate important differences in weed distribution change between CV and CA managed fields, as shown in Figure 8.

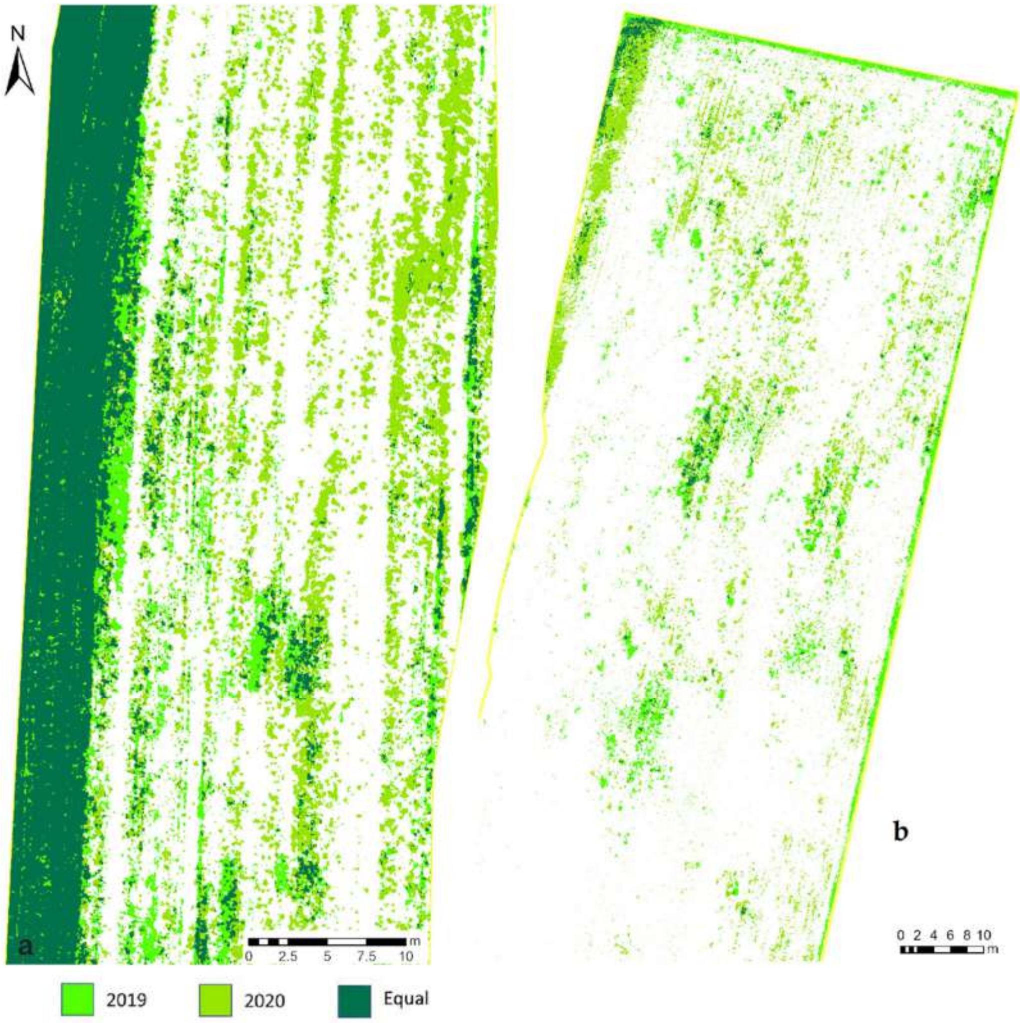

Figure 8. Differences in weed distribution change between the CA (**a**) and the CV (**b**) fields.

As shown in Figure 8, the percentage of area that was infested in both years is higher in the CA field (56.18%) than in the CV field (11.50%).

Removing the area near the CA field margin infestation drastically changed the percentages of infestation, as shown in Figure 9.

Excluding the field margin, the infested area in 2019 occupied 57.55 m^2, instead of 159 m^2 with field margin included. In 2020, the infested area excluding the field margin was greater than in 2019, reaching 128.29 m^2 (227.73 m^2 with field margin included). These results highlight the influence of the field margin on the weed infestation of no-till fields, and point out the necessity to pay attention to its management.

Excluding the field margin of the CA field, the area infested in both years was 28.90 m^2 that corresponded to 22.53% with respect to 127.94 m^2 that corresponded to 56.18% with the field margin.

Even though the area infested in both years was reduced by excluding the field margin effect of the no-till management field, in Figure 10 it can be seen that the CA field area infested in both years is still higher than that of the CV field. Indeed, excluding the field margin, the area infested in both years in the CA field was almost twice that of the CV field.

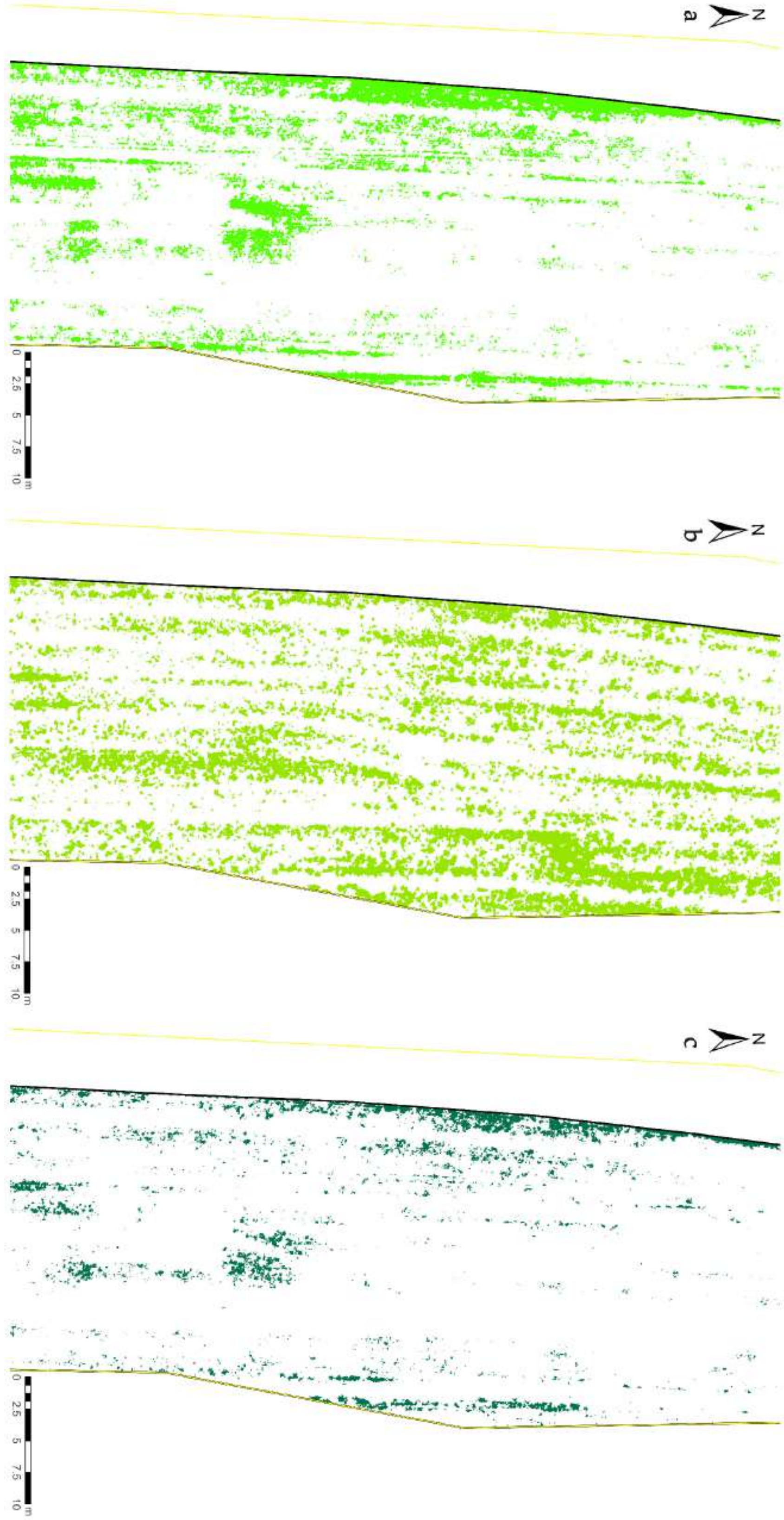

Figure 9. Weed presence in the CA field without the field margin in 2019 (**a**), 2020 (**b**), and in both years (**c**).

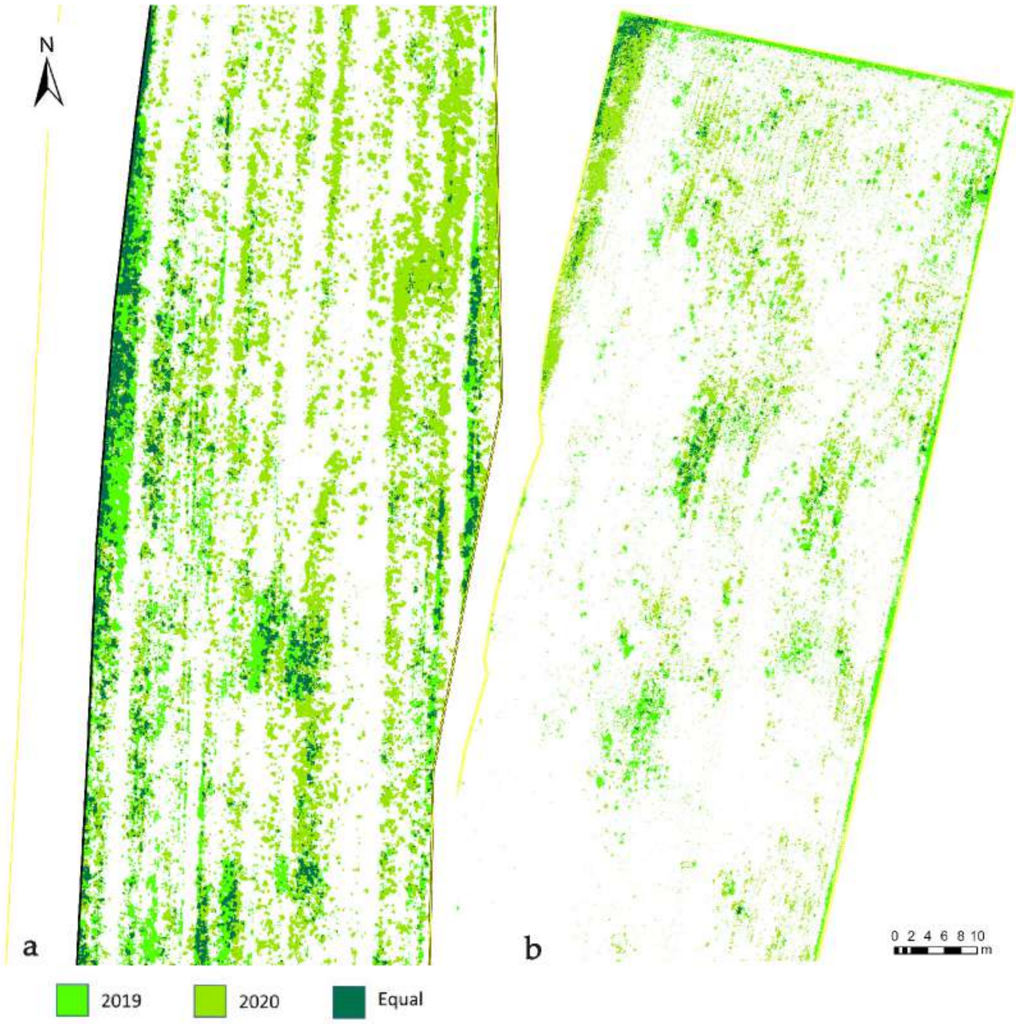

Figure 10. Differences in weed distribution change between the CA (**a**) and the CV (**b**) fields, excluding the CA field margin.

4. Discussion

Limited information about tracking the change in weed distribution comparing differently managed fields is documented in the literature, especially considering that most of the research is based on tracking invasive weed species' distribution change, which may have severe implications on human lives and agricultural production under the changing climate [40–42]. Yet both in Europe and globally, there is a rising trend in the use of modern technologies that are becoming ever more available and user-friendly to support precision agriculture, including weed monitoring for precision weed control [43]. Therefore, these technologies can be used in a rather simple but reliable way, to detect spatial changes in time in different field management systems, offering both scientific and practical information for decision-makers. The results obtained were expected; they are in accordance with what is known about the influence of soil management on the distribution of reproductive plant material [44–46].

Moreover, the two fields differ in weed species composition. While in the CV field the weed community mainly consists of *Sorghum halepense* and *Abutilon theophrasti*, in the CA field, there was a higher species richness consisting of *Digitaria sanguinalis*, *Abutilon theophrasti*, *Amaranthus retroflexus*, *Chenopodium album,* and small amounts of several other species. In contrast, the field margin was heavily populated with *Sorghum halepense*. This finding is in accordance with several studies indicating that no-till systems often have richer weed species communities compared to CV managed fields [47–49]. This difference in weed species richness could be one of the reasons for different field infestations between CV and CA fields; weeds can easily proliferate considering the abundance of precipitation during the study period. Moreover, the presence of an irrigation canal in the CA field is probably responsible for a highly developed field margin.

Still, the use of UAVs for weed detection in different agricultural systems is well known [28,50,51], as is the use of different algorithms, including MLC, that can recognize weed patches with a high degree of accuracy, enabling better weed control strategies [52–54]. Therefore, the results obtained by the approach used in this study indicates that UAVs and detection algorithms can be valuable tools for tracking weed distribution changes, even considering the specific realities of different cropping systems. Furthermore, in the future or in areas where experimentation is permitted, these maps could be used for aerial spraying weed control operations performed using a UAV [55] to indicate the areas more at risk of infestation.

Lastly, the edges of the fields are often observed to have a higher density of weed infestation than the more central areas of the fields [56]. This was particularly evident in the no-till field. This result is apparently related to a reduction in agricultural inputs near the field borders and/or the dissemination of weeds from the ditch and the surrounding landscape. This was very well observed in the CA field by the methods used in this study, and it strongly influenced the results. Since the field margin is considered a ruderal site and is managed differently compared to the field, good identification of the field margin obtained using the image analysis allowed its exclusion from further analysis. The comparison was repeated without considering the area of the CA field margin in order to include only the weed distribution data from the arable area.

5. Conclusions

The results obtained showed that the methodology for tracking weed spatial changes in time, as proposed in this paper, can be a reliable and very useful tool. Indeed, using the UAV and the identification algorithms it was possible to deduce the level of stability of weed patches over time in the fields under different management systems. Furthermore, the simplicity of this approach should allow stakeholders and decision-makers to apply it with minimal training. The results also point out the evident differences between spatial distribution in fields under different management conditions over time. While constant mechanical operations in the CV field seem to directly influence the seedbank and the transport of reproductive plant material across the field, those elements are not present or are severely reduced in the no-till system. Seeds disseminated or introduced in the fields under different agricultural systems experience different conditions, affecting their spatial distribution, germination, emergence, and longevity. Some of these specific conditions are the lack of seed burial and the permanent residual soil cover in the CA field, which are not present in the CV field. Considering that precision weed control using site-specific methods is already applied both in CV and in CA, changes in spatial distribution could affect the use of these methods. Considering the low stability of weed patches over time in CV, it would be imperative to perform UAV monitoring surveys every year in order to identify the weed patches for satisfactory site-specific weed control. However, if spatial aggregation for many weed species persists from year to year in no-till systems, maps made in one year could be used as a point of reference for precision weed control in the following years. Indeed, considering that weed patches in CA remain more stable, those specific areas of the field are quite suitable for weed development. In those places, weed–crop competition will be higher, resulting in severe yield loss. Therefore, it might be possible to have satisfactory weed control results in CA fields without the need to perform UAV surveys every year. Results obtained in this experiment also highlight another important issue of CA fields: the field margins. The influence of field margins on field infestation can be quite high; therefore, it is important to dedicate more attention to weed control practices applied close to the margin.

Further research is needed, including long term studies on many fields with different weed communities, to better understand changes in weed distribution over time and in different climatic conditions. Moreover, the temporal stability of patch distribution studies should consider species-specific behavior and also the influence of field margins. For all these possible future research studies, the methods described in this study provide an easy and highly precise solution.

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