Better-Weeds – Next generation weed management

Better-Weeds – Unkrautmanagement der nächsten Generation

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Abstract

Digitalisation in agriculture is currently expanding very rapidly. Digital field maps, geo-referenced machine movements, and a vast set of sensors on different platforms are already utilised on arable farms and even robotic field management is tested under practical field conditions. Digitalisation and artificial intelligence enable more effective and precise weed management through automated weed recognition. Sensor-based recognition systems automatically differentiate between weed and crop plants allowing for selective and site-specific weed control measures. By reducing herbicide inputs, site-specific herbicide application can mitigate negative impacts on the environment and reduce production costs.

With support from the Federal Ministry of Food and Agriculture (BMEL), the project “Better-Weeds” uses the technical possibilities of GIS-based imagery from unmanned aerial vehicles (UAV) and artificial intelligence (AI)-driven plant recognition on arable fields. The novel and innovative part of the project is a knowledge-based merging process. It combines the location data on the spatial distribution of different weed species with biological and ecological weed traits, as well as soil and climatic data to create extensive field maps. In addition, farm-specific agronomic conditions such as the crop rotation on the respective field and available weed control technology are considered. Together, this combined information is used to create a site-specific weed management plan for a given arable field taking into account weed control thresholds and the competitive ability and ecological benefits (e.g. habitat for beneficial insects) of the present weed species. The application of the generated management plan forms a step towards reducing reduce herbicide applications and increasing in-field weed diversity.

Keywords: automated flying, hotspot analysis, image recognition, knowledge-based maps, machine learning, mission planning, site specific weed management, Unmanned Aerial Vehicle, weed mapping

Zusammenfassung

Die Digitalisierung in der Landwirtschaft schreitet rasch voran. Digitale Feldkarten, georeferenzierte Maschinenbewegungen und eine Vielzahl von Sensoren auf verschiedenen Plattformen werden bereits in landwirtschaftlichen Betrieben eingesetzt. Sogar die Bewirtschaftung durch Roboter wird bereits in die Praxis überführt. Digitalisierung und künstliche Intelligenz ermöglichen zukünftig durch automatische Unkrauterkennung ein effektiveres Unkrautmanagement. Systeme unterscheiden automatisch zwischen Unkraut und Kulturpflanzen und ermöglichen so eine selektive und standortspezifische

Unkrautbekämpfung, die durch die Reduzierung des Herbizideinsatzes negative Auswirkungen auf die Umwelt vermindern und die anfallenden Produktionskosten verringern kann.

Mit Unterstützung des Bundesministeriums für Ernährung und Landwirtschaft (BMEL) nutzt das Projekt "Better-Weeds" die technischen Möglichkeiten von GIS-basierten Bildern aus Drohnen (UAV) und KI-gesteuerter Pflanzenerkennung auf Ackerflächen. Der neue und innovative Teil des Projekts ist ein wissensbasierter Fusionsprozess. Er kombiniert die Standortdaten aus der räumlichen Verteilung verschiedener Unkrautarten mit biologischen und ökologischen Unkrautmerkmalen sowie mit Boden- und Klimadaten, um umfassende Feldkarten zu erstellen. Darüber hinaus werden betriebsspezifische agronomische Bedingungen, wie z.B. die Fruchtfolge auf dem jeweiligen Feld und die verfügbare Unkrautkontrolltechnik berücksichtigt. Diese kombinierten Informationen werden genutzt um einen teilflächenspezifischen Unkrautmanagementplan zu erstellen, der die Schwellenwerte für die Unkrautkontrolle sowie die Konkurrenzfähigkeit und den ökologischen Nutzen (z.B. Lebensraum für Nützlinge) der auf dem Feld vorhandenen Unkräuter berücksichtigt. Der erstellte Managementplan ist ein notwendiger Schritt, um den Herbizideinsatz zu reduzieren und die Unkrautvielfalt im Feld zu erhöhen.

Stichwörter: Automatisches Fliegen, Bilderkennung, Hotspot Analyse, maschinelles Lernen, teilflächenspezifische Unkrautkontrolle, unbemannte Flugobjekte, Unkrautkartierung, wissensbasierte Karten

Introduction

Weed control on arable fields is currently predominantly carried out by uniform herbicide applications without a consideration of the spatial plant heterogeneity of the field and its weed distribution. Not only the decrease in floristic diversity on arable land in Germany (MEYER et al., 2013), but also the loss of insect diversity (HALLMANN et al., 2017) is associated with the use of herbicides in conventional agricultural systems. Thus, beneficial ecological functions such as the support of higher trophic levels and the delivery of ecosystem services such as higher pollination and biological pest control are associated with increased weed diversity (MARSHALL et al., 2003). In addition, a diverse weed species composition can have beneficial effects on crop yield (ADEUX et al., 2019). Against this background, new and especially environmentally friendly approaches to weed management need to be developed. The development of strategies for site-specific weed management (SSWM) plays a key role in reducing the negative impact of herbicide application on the environment.

One main advantage of SSWM is its potential to reduce herbicide inputs by up to 95%, a level that depends on crop and settings (TIMMERMANN et al., 2003; HAMOUZ et al., 2013; CASTALDI et al., 2017). This reduction in herbicide use results in economic advantages for the farmer (BARROSO et al., 2004) and mitigates negative impacts of pesticide application (KHAN et al., 2021) on the environment. In addition, SSWM may also contribute to an increased weed diversity in arable fields. SSWM belongs to modern and technologically-advanced agriculture and offers significant potential to control weeds by simultaneously reducing the environmental impact of pesticide application (NORDMEYER, 2006). SSWM includes a large range of techniques and practices including weed sensing systems, weed management models, and precision weed control implements (CHRISTENSEN et al., 2009) and digitalisation is a major driver for inventions in this field (HUANG et al., 2018; PFLANZ et al., 2018; SA et al., 2018; OLSEN et al., 2019; LATI et al., 2021). Even though the adoption of SSWM by farmers is still limited, the benefits and potential of SSWM has been demonstrated by numerous research projects all over the globe (HUNG et al., 2014; POHL et al., 2020; SELSKAB et al., 2021). In addition, technical innovations in the machinery sector such as single nozzle control for spot spraying or direct injection sprayers have been developed by different companies (POHL et al., 2020). Most of the SSWM techniques currently implemented by farmers for weed sensing mainly discriminate between crop and weed plants and are used to identify and localise weed patches. For this purpose, several technical approaches to discriminate between crops and weeds using different sensors and platforms have already been developed and exhibit a high level of precision (ESPOSITO et al., 2021). As a result, the first autonomous weeding robots come to practice in 2021.

However, weed plants play an important role for associated biodiversity on farmland (MARSHALL et al., 2003) i.e. by providing nectar and pollen for bees (BRETAGNOLLE and GABA, 2015) and other pollinator species. While some weed species possess a high value for associated higher trophic level and may therefore be tolerated in the field to increase overall biodiversity, others exhibit a high competitive ability and therefore require control. Identification and localisation of individual weed species in the field is therefore crucial for a species-specific weed management. In addition, the analysis of the spatial distribution of weed species and their specific functional traits, competitive traits, and population dynamics on crop fields should be further combined with local meta-information. In that way, sustainable weed management based on site-specific environmental characteristics of the field (e.g. soil and climate parameters) and farm-specific conditions is elaborated. The project “Better-Weeds”, started in 2021, tackles this challenge. Weed distribution maps, generated by automated image recognition using UAV platforms, are combined with information on weed traits and site-specific characteristics to generate knowledge-based field maps. A schematic presentation of the projects workflow is given in Figure 1. In the following, the necessary steps towards such a SSWM plan are described.

Figure 1 Schematic workflow of the project Better-Weeds

***Abbildung 1** Schema des Workflows im Projekt Better-Weeds*

Weed distribution maps

The implementation of SSWM relies on an accurate detection and mapping of weeds in the field. A wide range of sensors is used to detect weeds in the field, with most of them focusing on the general differentiation between crops and weeds (LATI et al., 2021). However, discrimination between the different weed species is required if specific species should be excluded from weed control measures. Recent studies indicate that great potential for weed identification lies in the use of image-based machine learning techniques in combination with remote sensing by unmanned aerial vehicles (UAV) (ESPOSITO et al., 2021). The images captured by the UAV are processed using artificial neural networks, e.g. deep-learning methods, which enable the identification of individual weed species (PETEINATOS et al., 2020). The challenge - especially when UAV are used - is to achieve a sufficiently high image resolution to identify single weed plants at the species level with sufficient efficacy to cover a complete field. Therefore, weed species are currently often identified on grid-arranged plots and the weed distribution is interpolated across the field (WELLHAUSEN et al., 2020). Within the project “Better-Weeds”, a two-step approach using a more appropriate UAV mission planning for the generation of weed distribution maps will be implemented. First, we use low-resolution images taken by UAV in combination with field-specific and landscape parameters to identify “hotspots” for weed management. These hotspots are characterised i.e. by high weed densities or site properties that can be used as indicators for a high weed species diversity. In the second step of the mission, the UAV-based weed survey will be concentrated on these hotspots by generating high-resolution images. With this approach, we aim to reduce the need for interpolation and enhance the proportion of identified plants on a field. By using autonomous mission planning, the technical requirements for the end users/farmers are minimised at this stage.

Knowledge-based maps

As long as weed management aims at a maximum level of weed control, the species identity is – in most cases – of minor importance. The farmers usually adjust their weed management decisions to the presence of major weed species such as *Alopecurus myosuroides* or *Galium aparine* that exhibit a high competitive ability. As most crop-selective herbicides control a broad spectrum of different weed species, other weed species of lower agronomic importance are simultaneously controlled when the entire field is sprayed with herbicides. By using knowledge-based field maps as a decision support system, SSWM can be efficiently employed not only for economic benefits (reduced herbicide inputs) but also for the aim of biodiversity conservation.

After generating the site-specific weed distribution map, additional species-specific information for the detected weeds will be added to this map. Weed functional traits are used to estimate the "value" of a specific weed species: *A. myosuroides* is highly competitive, fast spreading, and difficult to manage, while red list species like *Adonis aestivalis* with a low competitive ability exhibit limited negative impacts on crop production. Population dynamics of weed populations will also be considered as well as their importance in ecological networks. Additionally, site-specific characteristics of the respective field such as elevation, soil parameters, and the surrounding landscape will be included in the maps. Agronomic parameters like crop type, variety, and yield estimations are also part of the knowledge-based maps.

Management plans

Including an interpolated weed distribution map (Nordmeyer, 2006), the knowledge-based maps form the basis for generating the management plan of a specific field. An important step is the definition of specific ecologic, environmental and agronomic aims for the field: which weed species are regarded as problematic? Which are valuable? Which areas of the field should be treated with herbicides more intensively, which areas less intensively, and what kind of use is planned on the field in the subsequent years? Using the information on the technological capacities and restrictions of a farm, a weed management map for a specific year will be generated. Populations of common weeds should be reduced to a level that enables the population to survive without threatening the crop yield. This might be realised on parts of the field with lower expected yield levels or on parts of the field where weed management is difficult to conduct. Since more diverse weed populations tend to be less competitive (Storkey and Neve, 2018; Adeux et al., 2019), increasing the number of different weed species on a field will reduce weed competition over time.

Outlook

Within the project "Better-Weeds", we aim to develop a workflow to generate a site-specific weed management plan for a specific arable field. This weed management plan will entail the agronomic needs of the farm as well as the ecological aims for the field. All this will be based on global data management: the weed detection and mapping on the field, the definition of agronomic management aims by the farmers, the site-specific conditions as well as potential agronomic/technical restrictions. As a result, the weed management will be conducted less intensively, weed species populations sustain more stable, the environment less stressed and biodiversity will be maintained. Altogether, this plan will be fit for next-generation weed management.

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