UAV-based Field Monitoring for Precision Farming

UAV-basierte Feld Beobachtungen für die Präzisionslandwirtschaft

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Abstract:

To cope with an ever increasing demand for food and energy, we rely on a more effective and sustainable crop production in the future. To enable farmers and breeders to optimize their day-to-day crop management, they need to be provided with information about the actual status of their fields, e.g. the current status of the crop development or weed pressure. Unmanned aerial vehicles (UAVs) serve as an excellent monitoring platform for observing large areas of farm land in a comparably small amount of time. In this paper, we present a machine learning based approach for UAV imagery of different crop fields to analyze the spatio-temporal distribution of crop plants and weeds. We treat the crop-weed classification as a semantic segmentation using Convolutional Neural Networks and associate the image data over time allowing us to infer growth parameters and crop traits moving from canopy level to the level of individual plants.

Keywords: Crop Monitoring, Machine Learning, Precision Farming

Zusammenfassung:

Um dem ständig steigenden Bedarf an Nahrungsmitteln und Energie gerecht zu werden, müssen wir zukünftig auf eine effektivere und nachhaltigere Pflanzenproduktion setzen. Damit Landwirte und Züchter die tägliche Bewirtschaftung optimieren können, müssen sie über den aktuellen Zustand ihrer Felder informiert werden, z.B. über den aktuellen Stand der Pflanzenentwicklung oder den Unkrautdruck. Unbemannte Luftfahrzeuge (UAVs) dienen als Überwachungsplattform, um große Flächen in vergleichsweise geringer Zeit zu beobachten. In diesem Beitrag behandeln wir die Analyse von UAV-Bildern hinsichtlich der automatischen Erfassung der raumzeitlichen Verteilung von Nutzpflanzen und Unkräutern. Wir verwenden für die Klassifikation eigens für den Agrarbereich optimierte maschinelle Lernverfahren und verknüpfen die analysierten Bilddaten über mehrere Zeitpunkte, sodass wir auf Wachstumsparameter und Merkmale schließen können, welche sich auf den Bestand und auf einzelne Pflanzen beziehen.

***Deskriptoren:** Agrarrobotik, maschinelles Lernen, Präzisionslandwirtschaft*

1 Introduction

The increasing demand for food and energy induced by an ever-growing world population is a global challenge. A high and stable crop production is key to satisfy these needs, but arable land is limited and the environmental footprint of agricultural production needs to be reduced. Agrochemicals are intensively used in conventional agriculture for effective weed control and to attain high yields. Whole fields are typically treated uniformly with a single herbicide dose, spraying the soil, crop and weed in the same way. Agrochemicals, however, can have a negative impact on the environment and biodiversity, and consequently affect human health (HORRIGAN et al. 2002). For the development of more effective crop cultivars and crop production strategies, we have to increase our understanding about the crop and its interaction with the environment.

Thus, an effective and future-oriented agriculture needs to focus on both high productivity and sustainability. One major goal of sustainable farming is to increase yield while reducing the reliance on agrochemicals. Precision farming techniques seek to address these conflicting targets by (i) monitoring fields for key indicators of crop health, spatial distribution of crop traits and weeds and (ii) providing targeted measures for selectively treating only those plants that actually need it. By monitoring the field status and automatically inferring statistics about the development of the crops, we can gain a better understanding about the growth process and at the same time minimize the use of applied agrochemicals (WALTER *et al.* 2018).

Fig. 1: Left: UAV system (DJI Inspire II). Right: Sugar beet field in early season analyzed with our approach. We estimate the spatial distribution of crop (green) and weed (purple) and the per-plant canopy cover. This information directly leads to concrete suggestions for the farmers.

A popular way to monitor farmland is through the use of aerial vehicles such as UAVs. UAVs can cover large areas in a comparably short amount of time without interacting with the environment as ground vehicles do. For an effective on-field intervention, it is important to know the spatial distribution of the weeds on the field already at an early state. The earlier mechanical or chemical weeding actions are executed, the higher the chances for obtaining a high yield. A prerequisite to trigger weeding and intervention task is a detailed knowledge about the spread of weeds. Additionally, UAVs can be employed over an entire crop season to monitor important traits for the crop plants. This provides a temporal dimension to monitoring of the field which is necessary for understanding how the field status is evolving and to trigger certain field management tasks. For breeders, the monitoring of genotype performance within field selection trials is a crucial part for the development of better varieties. Presently, this analysis is mostly done manually, which is laborious. Therefore, it is important to have an automatic perception pipeline that monitors and analyzes the crops automatically and provides a report about the status of the field over time.

2 Material und Methods

In this work, we address the problem of analyzing RGB-only imagery captured by UAVs to inspect the status of a field in terms of the spatio-temporal crop and weed distribution. We treat the classification problem as one of semantic segmentation (BADRINARAYANAN *et al.* 2017) providing a pixel-wise classification of the entire image by using state-of-the-art **F**ully **C**onvolutional Neural **N**etworks (FCNs). We focus on the detection on a per-plant basis to estimate the amount of crop plants as well as various weed species. We furthermore associate the data obtained by multiple UAV flight sessions over the crop season and can provide information of dynamic crop development over time directly to the farmers and breeders. The experiments show the performance of our plant classification system on several crop fields under different acquisition conditions. Our approach efficiently adapts to different crop and weed species with comparably small amount of training data. We demonstrate that we are able to exploit classifier output, i.e., the spatial and the semantic field information, (i) to associate the acquired data over multiple UAV flight sessions and (ii) to extract canopy cover over time.

2.1 Vision-Based Plant Classification using FCNs

The main goal of our vision-based plant classification system is to segment the plants and weeds in UAV images to estimate their spatial distribution in the field and to allow for their precise and individual mapping. Our classification further serves as a basis for inferring growth parameters and crop traits moving from canopy level to the level of individual plants. The classification system used in this work is based on our previously published FCN approach in LOTTES *et al.* (2018) with slight modifications such that it can deal with *RGB-only* input as well as work on images with a size of 1500x2000 pixels. **Fig. 1** and **Fig. 4** illustrate exemplary outputs of our classification system.

SLAUGHTER *et al.* (2008) state that a major challenge for vision-based plant classification systems in agricultural fields is their adaptation to changing conditions such as different crop and weed types in new fields and rapidly changing environments. These changes lead to a different distribution of the data which may not be properly modeled by the classifier. This holds especially for UAV images as they are directly affected by natural illumination conditions (**Fig. 4**). To address these challenges, we apply supervised transfer learning, i.e., fine-tuning a pre-trained model, to adapt the classifier to new environments. We achieve a good transferability by using a comparably small amount of labeled training data of the new field.

2.2 Semi-Supervised Rapid Labeling

Labeling of images with pixel accuracy is a laborious task, which is not scalable from a practical application point of view. Therefore, we propose two strategies to rapidly obtain labeled data for a new field in a semi-supervised way. For both strategies, we first segment the vegetation from the background, i.e. soil, by using a threshold based approach applied to the Excess-Green-Index (MEYER AND NETO 2008, KHANNA *et al.* 2015). The output from this step is a binary image representing vegetation and soil.

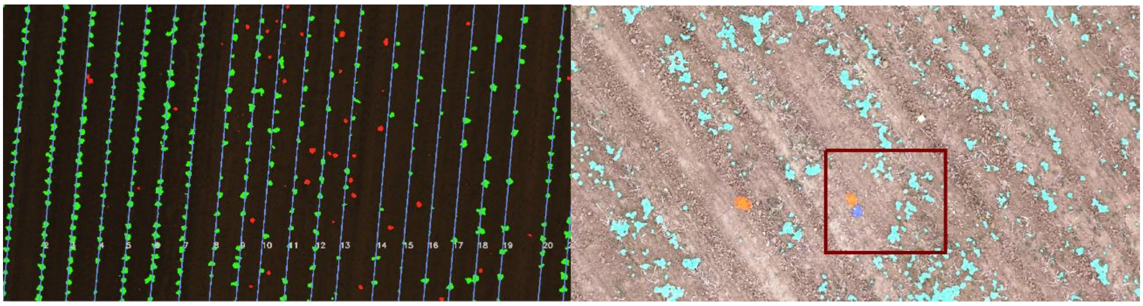

Fig. 2*:* Left: Labeling strategy based on crop row detection. Right: Labeling strategy using Random Forest. We only manually annotated the vegetation pixels within the red box.

The first approach **(Fig. 2)** for semi-automated data labeling is to exploit the crop row structure. We employ a variant of the Hough transform on the binary vegetation image as proposed in (LOTTES *et al.* 2017b) providing us the crop rows in the image. We then automatically assign the label crop to all vegetation pixels within a certain threshold distance to the estimated crop row. Remaining vegetation pixels in the image are considered to be weeds. A limitation of this strategy is that weeds located along the crop row are wrongly labeled. Despite the rough labeling procedure, our FCN classifier is able to adapt to new field conditions.

In case a field has no strict crop row structure **(Fig. 2)**, we follow strategy two employing a standard Random Forest (RF) classifier (BREIMAN 2001) that is capable of solving multi-class problems. Here, we exploit the fact that RF can be trained with a comparably small amount of data and use it to rapidly produce predictions. For the features, we are using the ones proposed in our earlier work (LOTTES *et al.* 2017a). To initialize this procedure, the user only has to provide a few labels for some of the vegetation pixels, which are then used to train the RF. Then, in the prediction step, the RF provides labels for the entire vegetation mask.

2.3 Temporal Image Data Association

Nowadays, commercial UAVs are typically equipped with low cost GPS sensors providing a global positioning accuracy of around 5-10m. However, the monitoring of growth parameters of individual plants requires a temporal data association at centimeter level accuracy. A common technique to obtain a more precise image registration is by matching visual descriptors computed on the images. Such descriptors, however, are not suited to cope

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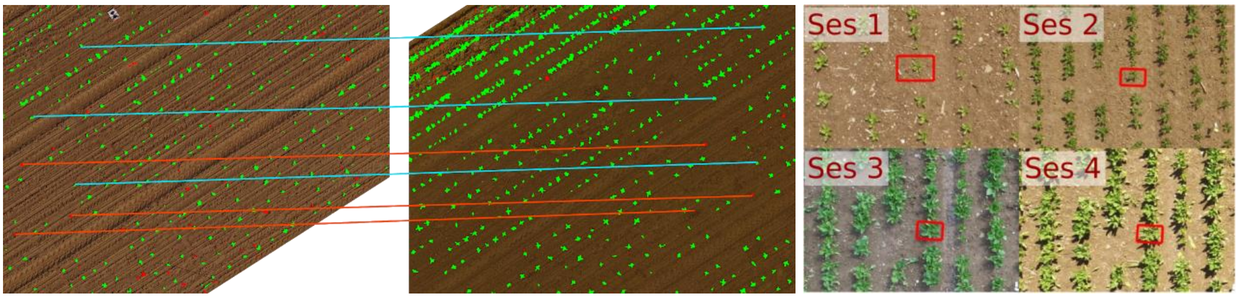

Fig. 3: Data association between images with a temporal difference of one week. We only allow crops to match with crops (blue) and weeds with weeds (orange). Note, we only visualize a few correspondences.

with the large differences in appearance such in agricultural environments over time, which leads to an unreliable registration.

With the presented approach we are able to obtain a temporal correspondence between the image data by exploiting the distribution of crop and weed locations as well as the semantic information obtained from the FCN classification. The details of our approach are described in (CHEBROLU *et al.* 2018). It allows to register images with the accuracy required for a plant-wise data association (**Fig. 3**). We use the classification results to allow only correspondences between same class labels. Given the associations, we are able to register the two images in a common reference frame and compare different plant properties such as canopy cover or class labels.

To illustrate the data association on plant level, we draw a box around a specific crop in **Fig. 3** (right). Given that we registered the image data temporally, we can track the same plant across multiple sessions as visualized by the red boxes. By this we can monitor and compute growth parameters on a per-plant basis over the whole field.

3 Experiments

The experiments presented here, demonstrate the ability the approach to detect different crop and weed types in aerial RGB imagery. Even, with limited training data, our FCN classifier is able to adapt to the new situations. Furthermore, we show two exemplary applications, where the temporal data association supported by the classifier output enables us (i) to monitor the development of individual plants in the field over time and (ii) to analyze the effect of fertilization in crop fields.

3.1 Crop-Weed Detection in Different Crop Fields

For the evaluation of the crop-weed detection performance, we acquired image data from multiple crop fields using different UAV systems. Tab. 1 summarizes the datasets used in this paper. We use the software package METASHAPE (Agisoft) to register the single images captured during a UAV flight and compute the orthomosaics for each field. To obtain an appropriate image size for further analysis with the FCN classifier, we cut the orthomosaics into tiles (ortho-tiles) of size 1500x2000 pixels (**Fig. 4**). For each

ISSN 0947-7314

dataset, we labeled five ortho-tiles using the labeling strategies described in Sec. 2.2 to obtain the training data. For all experiments, we fine-tuned the same pre-trained FCN, which was trained on independent data from different fields from our previous publication (LOTTES *et al.* 2017b).

We evaluate and report the segmentation performance on a per pixel basis. To obtain the performance metrics, we thoroughly labeled 10 ortho-tiles for each dataset forming a high quality ground truth. The accumulated average precision (P) and recall (R) values are shown in **Tab. 1**. As average, we consider the respective means of the class-wise P/R values, i.e., for crop, weed, soil, and toxic weed. Our evaluation suggests that we are able to obtain a recall of **87**% and a precision of **84**% over all datasets. For the peppermint dataset, we achieved class-specific recall of **95**% for the toxic weeds. This is crucial for the farmers as they need to guarantee that the quantity of toxic weeds in the field is below a permissible limit.

Tab. 1: Key parameters of the datasets and classification performance using recall (R) and precision (P)

	UAV	*Images*	*Tiles*	*GSD*	*Classes*	*avg. R*	*avg. P*
Sugar beet	DJI Mavic	192	42	8mm	Crop, weed, soil	83%	81%
Pumpkin	DJI Inspire II	219	80	5mm	Crop, weed, soil	85%	81%
Strawberry	DJI Inspire II	75	59	3mm	Crop, weed, soil	95%	85%
Peppermint	DJI Phantom 4	330	165	5mm	Crop, weed, toxic weed, soil	88%	86%

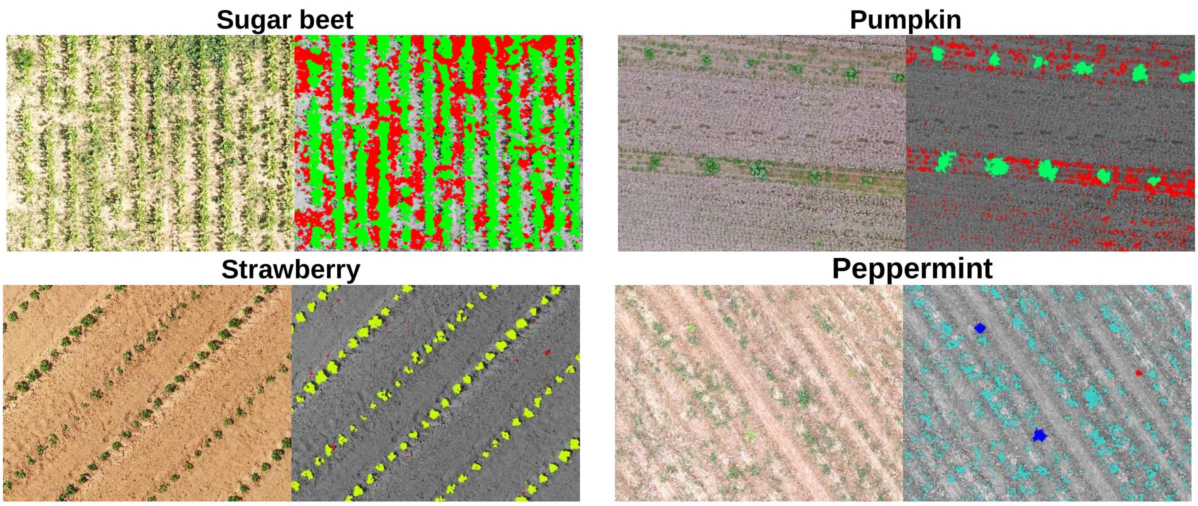

Fig. 4: Per Crop: RGB-tiles (left) of size 1500x2000 pixels cropped from the orthomosaic and analyzed images (right). Colors refer to different classes, i.e., sugar beet / pumpkin (green), strawberry (yellow), peppermint (bright blue), toxic weeds (blue), and general weed (red)

3.2 Monitoring Early Crop Growth as Affected by Nitrogen Status

The variation of canopy cover within a field reflects differences between growth factors which are often soil moisture and nutrient availability, among which nitrogen plays a vital role. Therefore, detection of growth differences in early stages enables site-specific management such as variable rate fertilization or precision spraying of pesticides.

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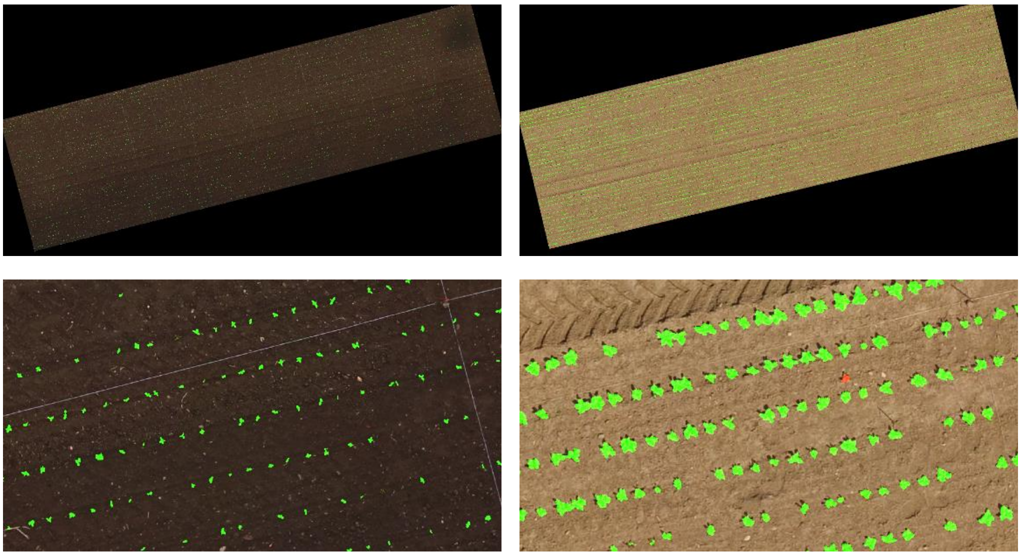

Fig. 5: Top row: Orthomosaics of sugar beet field recorded on the 25th April (left) and the 18th May (right) in 2017. Bottom row: The same zoomed area.

This experiment illustrates that we are able to analyze the effect of fertilizer on the growth of sugar beets at an early growth stage based on UAV images. The field trial consisted of 4 nitrogen fertilization regimes (0, 40, 80 and 120 kg N/ha) with 6 plot replicates of 36m² each. A detailed description of the experimental field setup is also described in Sa *et al.* 2018. We acquired images with a UAV on two dates, on 25th April (39 days after sowing, DAS) with a *DJI Inspire II* and on the 18th May (62 DAS) with a *DJI Matrice 200*, corresponding to an average growth stage of BBCH of 12 and 16, respectively. **Fig. 5** illustrates the two orthomosaics from the respective acquisition dates as well as the arrangement of the plots. After performing the classification of the sugar beets and weeds, we used our data association procedure as described in **Sec 2.3** aligning the two orthomosaics to automatically derive the growth parameters for the same area of interest.

To analyze the growth, we monitor the canopy cover (**Fig. 6**) as a proxy and correlate it with the amount of fertilizer applied to the plots. Plants count per area and canopy cover are important parameters to evaluate crop performance, vitality and estimate potential yield. Both parameters are of particular interest during early growth stages. The number of plants is a result of the germination rate and the young plant survival. Canopy cover at a given time reflects growth of the crop integrating biomass, leaf area, number of leaves as developed until image acquisition. We compute the total canopy cover (TCC), which is the surface in a plot covered by classified sugar beets as well as the average canopy cover (ACC), which is TCC divided by the number of single plants in a plot. We observe increased growth up to 80 kg N/ha, whereas higher N fertilization did not result in further growth of the sugar beets. This trend is already visible in the TCC from at the 25th April.

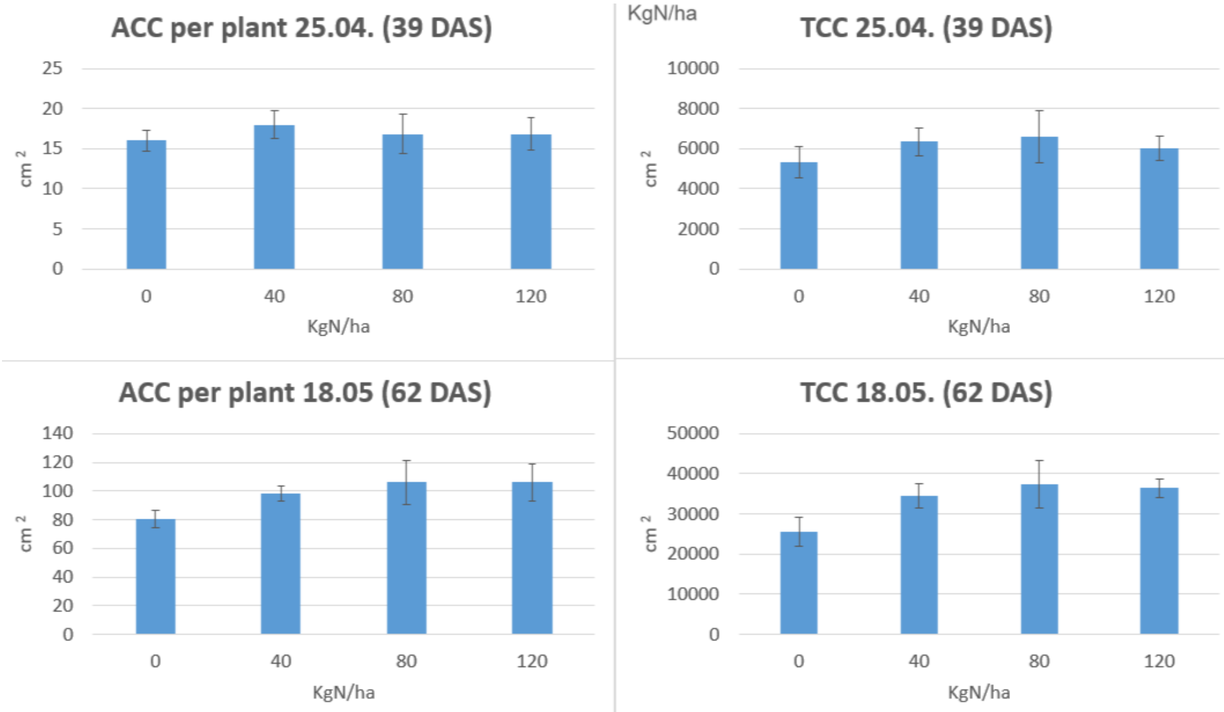

Fig. 6: Total and average canopy cover per plant as affected by Nitrogen fertilizer treatment.

4 Discussion and Conclusion

In this paper, we propose a UAV-based plant classification system for crop monitoring enabling precision agriculture applications by automatically inferring growth parameters and crop traits moving from the canopy level to the level of individual plants. We show the ability of the classifier to identify multiple crops and weed types under different environment conditions. As an application, we study effects of fertilization by analyzing canopy cover data obtained by our classification system. The results indicate that these measurements might enable site specific fertilization in crops at an early growth stage and can be used when methods based on canopy reflectance or greenness are failing due to a low canopy coverage. Furthermore, such a system can potentially support soil sampling based fertilization strategies which are often limited in spatial representation due to a high labor and financial costs of the soil sampling and lab analysis. Such applications are done in sugar beets, but also in winter cereals.

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References

BADRINARAYANAN, KENDALL, CIPOLLA (2015): SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 39, iss. 12, pp. 2481-2495.

BREIMAN (2001): Random forests*.* Machine Learning, 45(1):5–32.

CHEBROLU, LÄBE, STACHNISS (2018): Robust Long-Term Registration of UAV Images of Crop Fields for Precision Agriculture, IEEE Robotics and Automation Letters, vol. 3, iss. 4, pp. 3097-3104.

HORRIGAN L, LAWRENCE RS, WALKER P (2002): How sustainable agriculture can address the environmental and human health harms of industrial agriculture. Environ Health Perspect, 110:445–56.

KHANNA, MÖLLER, PFEIFER, LIEBISCH, WALTER, SIEGWART (2015): Beyond point clouds - 3d mapping and field parameter measurements using uavs. In Proc. of the IEEE Int. Conf. on Emerging Technologies Factory Automation (ETFA), pages 1–4.

MEYER, NETO (2008): Verification of color vegetation indices for automated crop managing applications. Computers and Electronics in Agriculture, 63(2):282 – 293.

LOTTES, HÖFERLING, SANDER, STACHNISS C. (2017A): Effective vision-based classification for separating sugar beets and weeds for precision farming. Journal of Field Robotics.

LOTTES, KHANNA, PFEIFER, SIEGWART, STACHNISS (2017B): UAV-Based Crop and Weed Classification for Smart Farming. In Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA).

LOTTES, BEHLEY, CHEBROLU, MILIOTO, STACHNISS (2018): Joint Stem Detection and Crop-Weed Classification for Plant-specific Treatment in Precision Farming. In Proc. of the IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS).

SA, POPOVIĆ, KHANNA, CHEN, LOTTES, LIEBISCH, NIETO, STACHNISS, WALTER, SIEGWART (2018): WeedMap: A Large-Scale Semantic Weed Mapping Framework Using Aerial Multispectral Imaging and Deep Neural Network for Precision Farming. Remote Sens. 2018, 10(9), 1423.

SLAUGHTER, GILES, DOWNEY (2008): Autonomous robotic weed control systems: A review. Computers and Electronics in Agriculture, 61(1):63 – 78.

WALTER, KHANNA, LOTTES, STACHNISS, SIEGWART, NIETO, LIEBISCH (2018): Flourish-A robotic approach for automation in crop management. Conference paper. At 14th International Conference on Precision Agriculture.

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