Flourish - A robotic approach for automation in crop management

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Abstract. *The Flourish project aims to bridge the gap between current and desired capabilities of agricultural robots by developing an adaptable robotic solution for precision farming. Combining the aerial survey capabilities of a small autonomous multi-copter Unmanned Aerial Vehicle (UAV) with a multi-purpose agricultural Unmanned Ground Vehicle (UGV), the system will be able to survey a field from the air, perform targeted intervention on the ground, and provide detailed information for decision support, all with minimal user intervention. The system can be adapted to a wide range of farm management activities and to different crops by choosing different sensors, status indicators and ground treatment packages. The research project thereby touches a selection of topics addressed by ICPA such as sensor application in managing in-season crop variability, precision nutrient management and crop protection as well as remote sensing applications in precision agriculture and engineering technologies and advances.*

This contribution will introduce the Flourish consortium and concept using the results of three years of active development, testing, and measuring in field campaigns. Two key parts of the project will be shown in more detail: First, mapping of the field by drones for detection of sugar beet nitrogen status variation and weed pressure in the field and second the perception of the UGV as related to weed classification and subsequent precision weed management.

The field mapping by means of an UAV will be shown for crop nitrogen status estimation and weed pressure with examples for subsequent crop management decision support. For nitrogen status, the results indicate that drones are up to the task to deliver crop nitrogen variability maps utilized for variable rate application that are of comparable quality to current on-tractor systems. The weed pressure mapping is viable as basis for the UGV showcase of precision weed management. For this, we show the automated image acquisition by the UGV and a subsequent plant classification with a four-step pipeline, differentiating crop from weed in real time. Advantages and disadvantages as well as future prospects of such approaches will be discussed.

Keywords. *Precision agriculture, variable rate application, Nitrogen fertilizer demand, weed classification and detection, remote sensing, imaging, unmanned aerial vehicles*

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Introduction

Increasing the use efficiency of resource inputs is a major challenge in modern agriculture to simultaneously optimize the farm profitability while environmental impacts can be decreased. A prominent example is the use of nitrogen (N) fertilizer, which is applied to most crops worldwide to facilitate or maintain high yields. As it was recently shown, N fertilization can account for up to 40% of the ecological footprint of cereals from which bread is produced (Goucher et al. 2017). Another important challenge of contemporary agriculture is to reduce application of pesticides.

Precision farming tools such as variable rate application and site specific treatments are commercially available. Today, they are often already facilitated by proximal or remote sensing techniques, but often these techniques are related to company specific calibrations or narrow time windows of application, are restricted to certain crops and/or are difficult to compare to other techniques or products, because the mechanisms and models that underlie data processing are not made available to the public.

The basic idea of the Flourish project has been to combine cutting edge technology in proximal sensing with upcoming, autonomous ground intervention possibilities and to analyze the potential of such a combination for cultivation of a relevant arable crop (Liebisch et al. 2016). The concrete aim was to combine the aerial survey capabilities of a small autonomous multi-copter Unmanned Aerial Vehicle (UAV) with a multi-purpose agricultural Unmanned Ground Vehicle (UGV). This 'team' of two autonomous machines should learn to survey a field from the air, perform targeted intervention on the ground, and provide detailed information for decision support, all with minimal user intervention (Fig. 1). The system should be adapted to a wide range of farm management activities and to different crops by choosing different sensors, status indicators and ground treatment packages.

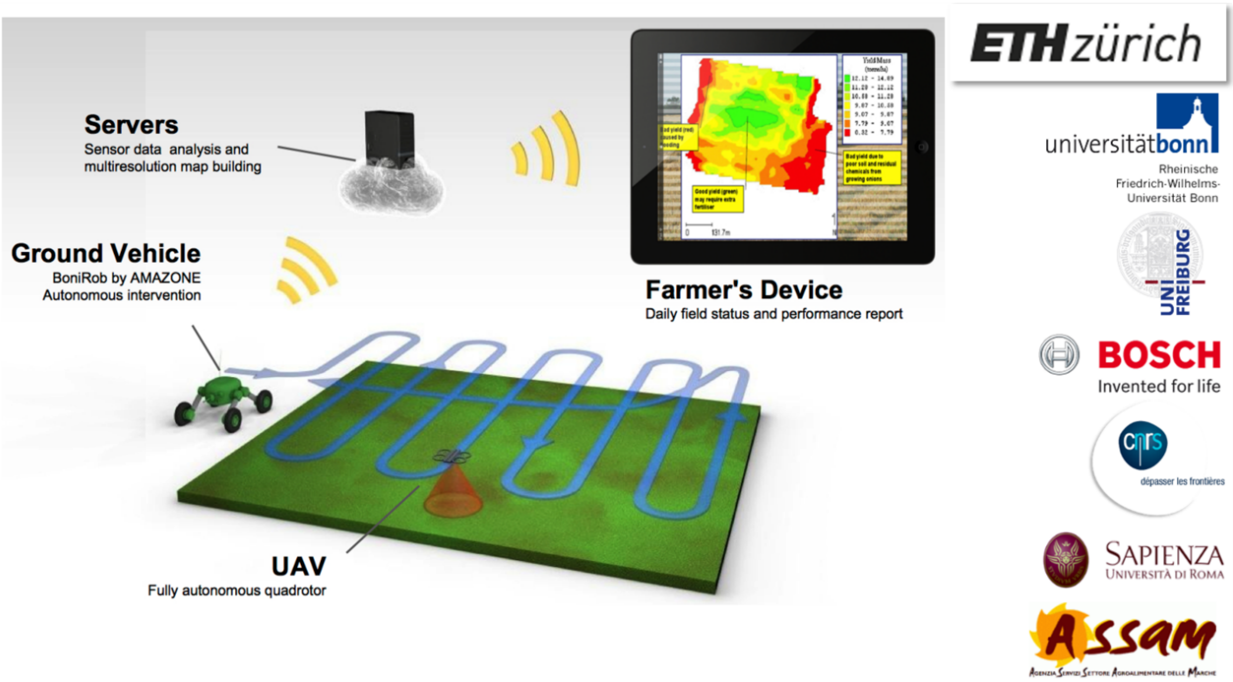

Fig. 1. The idea and consortium of the 'Flourish' Project (2015-18) a Robotic and Automation solution for precision agriculture. http://flourish-project.eu

Sugar beet was used as the model crop for most studies within the framework of the Flourish project. Sugar beet is a commonly strongly fertilized high-value crop widespread in temperate regions and – due to its development from a tiny seed – it requires intense control of weeds, turning it into an ideal research object for minimization of herbicide and N application. Adjusting N fertilization precisely to the plant's demand is of special importance for sugar beet for two reasons: First, N deficiency causes yield losses; second, excess N reduces the extractable sugar content (Hofmann 2005) and increases the susceptibility to pests and diseases.

Equipment, field sites and methodology

The here presented case studies were performed by consortium members within the framework of the Flourish project. More and additional information can be found in the cited papers or on the related project homepage (Flourish 2018, http://flourish-project.eu). The core robot team used in the consortium consists of a modified DJI Matrice 100 UAV and a Bonirob from Bosch (Fig. 2). Most of the experiments and the final use case applications are operated and optimized for these platforms. However, many other UAVs and UGVs and specific sensors are used for method development and in-depth studies as necessary and available by each partner. For this study, two different UAVs were used as described below.

Fig. 2. Unmanned Ground Vehicle Bonirob, carrying an Unmanned Aerial Vehicle.

Estimating Nitrogen Fertilizer demand study

A randomized field trial with six plot replicates (6 x 8 m) was established in a commercial sugar beet field and three Nitrogen (N) input treatments were applied. Treatments received either 0, 40 or 80 kg N ha^{-1}, respectively, additional to soil available N, that was determined prior seeding by the N_{min}-method (Fig. 3). All plots were treated with herbicides and fungicides according to common practice. At harvest, five beets per plot were sampled for determination of yield (Y) and quality parameters, such as extractable sugar content (ESC). The sugar yield (SY) was calculated according to equation 1 (For more details see Liebisch et al. 2016 and Pfeifer et al. 2016).

$$SY = Y*ESC \quad (1)$$

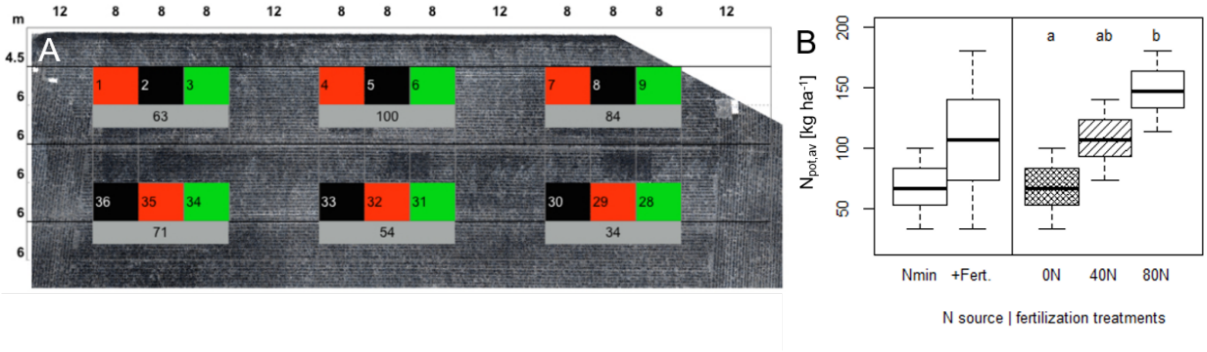

Fig. 3. A randomized field trial with six plot replicates (6 x 8 m) marked with colors (A). The three N input treatments: 0, 40 or 80 kg N/ha are shown in black, green and red, respectively. Soil available N determined prior to seeding by the Nmin-method for each block is shown in the grey bar below. Potentially available N as affected by the soil N stock or fertilization treatment is shown in (B)

For ground reference data a series of measurements and samplings were performed on a regular basis between 18.05.2016 and 23.06.2016. The presented data comprise above ground biomass N concentration (N_{conc}) and total N uptake (N_{tot}); N_{tot} was calculated as the above ground biomass multiplied by N_{conc}.

Spectral reflectance on ground level (proximal) was recorded with an ASD Fieldspec 4 (ASD Inc., Boulder, USA). A reflectance standard (Spectralon) was used to compensate for the effect of variable incoming sunlight irradiation (Müller-Ruh et al. 2017). Aerial image spectroscopy was realized with a Gamaya VNIR 40 camera (Gamaya, SA, Lausanne, Switzerland) mounted on a Solo drone from 3D Robotics, Inc, USA (Fig. 4 C). For the two spectral devices (for more details see Liebisch et al. 2016), a set of spectral indices was calculated, related to ground truth. In this paper, we discuss the simple ratio (SR) in detail, because it is used for detection of crop N status in ground and aerial sensing approaches (e.g. Gnyp et al. 2016). For other spectral N indicators see Pfeifer et al. (2016) and Müller-Ruh et al. (2017).

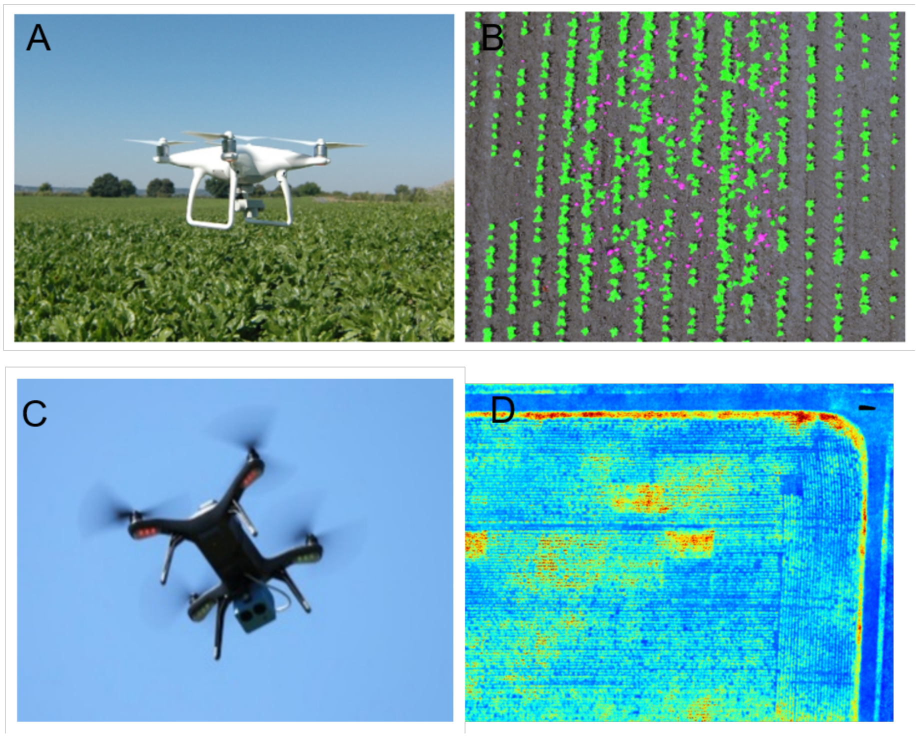

Fig. 4. A commercial quadrocopter used for RGB image acquisition (A) for development of weed detection algorithms (B); another commercially available quadrotor platform mounted with a Gamaya camera system (C) and a derived false color map indicating N status in sugar beet (D).

Weed tracking from UGV and UAV

For the UGV based weed detection studies, different versions of BOSCH's Bonirob (Bosch, Renningen, Germany) system, equipped with a 4-channel JAI camera (JAI group, Copenhagen, Denmark), were used. For the UAV based weed classification shown here a commercially available DJI Phantom IV with an integrated RGB camera was used. The weeds were detected using a four-step-approach (for details see Lottes et al. 2016; Lottes et al. 2017). In brief, the first step consists of the segmentation between vegetation and soil based on RGB and normalized difference vegetation (NDVI) images. In the second step, the masked vegetation is analyzed for a set of features, taking into account local neighborhoods of relevant image regions. Multiple parameters describing the shape of a small patch of vegetation, but also parameters embedding the vegetation into a putative spatial sowing pattern and so-called 'statistical features' for color information of the vegetation are calculated. The third step then consists in a random forest classification of the vegetation based on the features extracted in the previous step. This means that statistical procedures, taking into account all of the calculated parameters, are applied to determine the probability, with which a certain region within the vegetation mask belongs to a certain class of plants (crop or weed a or weed b, depending on training data input). In the final step, Markov Random Field procedures are applied to smooth the results and to determine finally, whether a connected entity of vegetation is a crop or one of the weeds, resulting e.g. in color coded maps that show crops in green and weeds in a different color (Fig. 4B and Fig. 5).

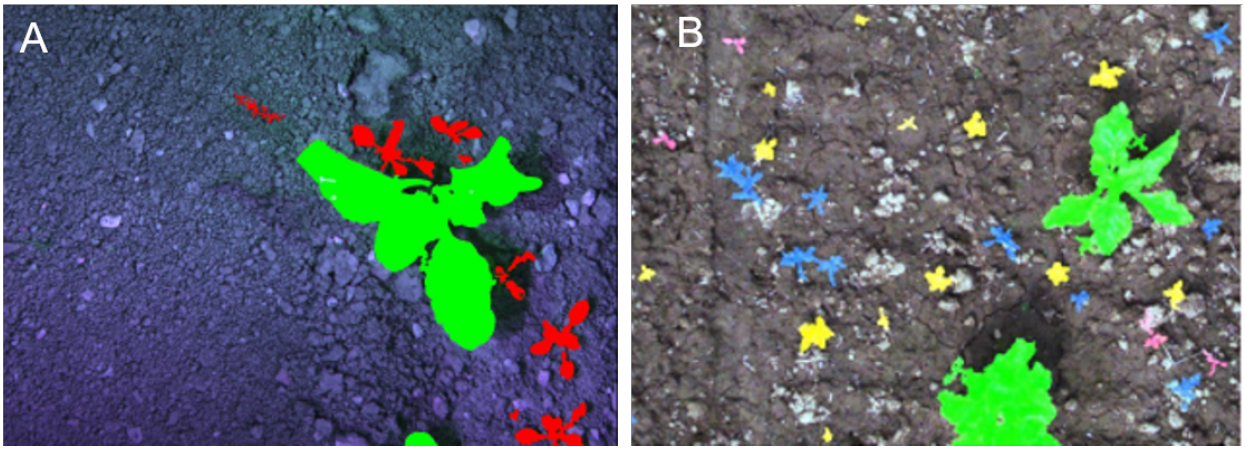

Fig. 5. Examples of crop-weed-classification results: Results based on images acquired with (A) the JAI camera mounted on the UGV (published in Lottes et al. 2016) and with (B) a RGB camera mounted on a DJI Phanom UAV (published in Lottes et al. 2017). Green depicts the sugar beet crop and red, blue, yellow and magenta show different weed species, respectively.

Results and Discussion

Aerial estimation of N fertilizer demand

The treatments established in the field experiment reflected the N status ranging from moderately deficient to non-limiting, while maximum sugar yields were likely not yet reached (Fig. 6). Highest yields in the test region reached 100 t ha^{-1}, which is in the range of highest yields obtained in this study. The highest obtained sugar yields of around 20 t ha^{-1} reflect a very good result for most field conditions.

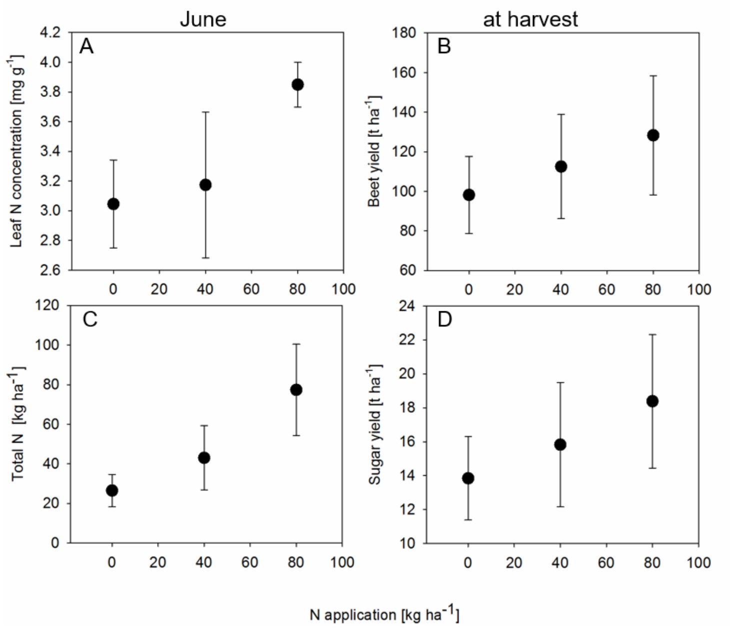

Fig. 6. Experimental treatments reflect realistic variation of N-status in the vegetative growth phase (A and C) and related sugar beet yield parameters (B and D).

The SR proved very useful to indicate plant N status (N_{tot}) (Fig. 7); demonstrating the applicability of spectral sensing methods for detection of N fertilizer demand in sugar beets. Comparison of SR derived from ground based spectrometer measurements with the camera-derived SR, showed very good correlation. Differences can be related to methodical differences in spectral calibration, atmospheric effects between sensor and target and varying sensor specifications, such as band width. However, both spectral measurements proved appropriate to quantify N fertilizer demand.

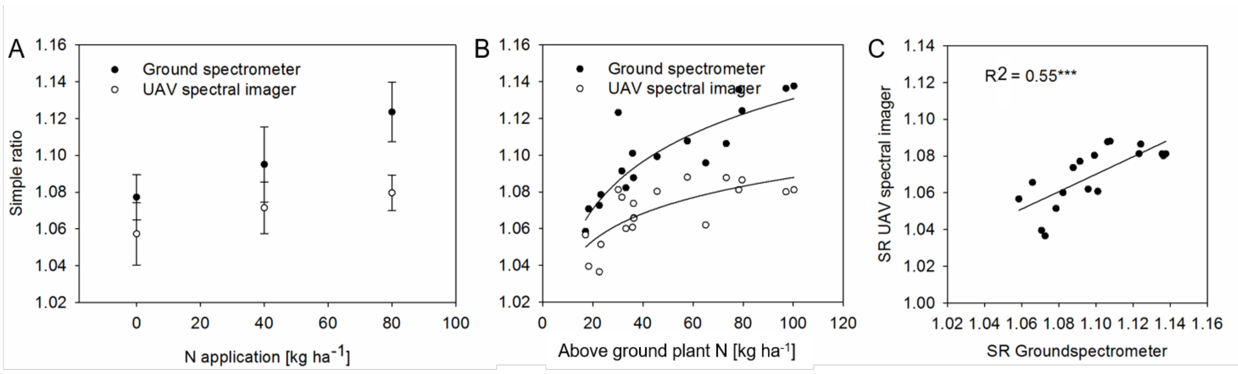

Fig 7. The spectral N status indicator Simple Ratio (SR) as affected by N application (A) and Total N in the above ground biomass (B) shown for the ground and UAV based spectral measurements. The relationship between the ground based spectrometer and UAV spectral measurements is shown in (C).

Weed identification

Receiver Operating Characteristics (ROC) curves and Precision-Recall (PR) plots (Fig. 8) were assembled based on the data obtained from UAVs and UGVs. ROC curves show the relation between true positive and false positive rates at different thresholds, whereas PR-plots show the derived ratios of true positive rates over the sum of true positive and false positive (Precision) and true positive and false negative (Recall), respectively. Results taken from UAVs (Lottes et al. 2017) showed that it is possible to cover larger field areas rapidly and to spot out regions that require closer investigation. Based on images taken by the UGV, high-precision localization of weeds was then performed and it was shown in the consortium that these maps provide the necessary resolution to treat weeds mechanically or apply herbicides in a site-specific manner. In all data sets, taking into account the equidistant sowing pattern for sugar beet improved the differentiation between crop and weeds.

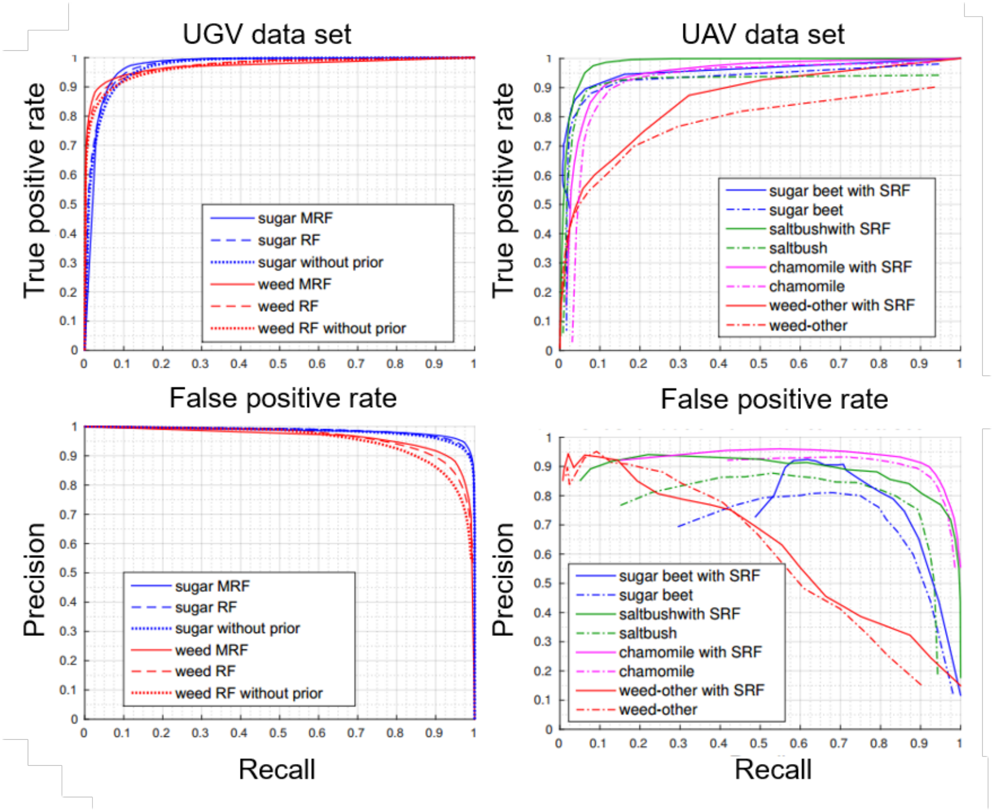

Fig. 8. ROC cross validation curves and precision recall cross validation of a UGV and UAV data set, respectively. The term label "RF" refers to random forest-only classification and "MRF" to the combination of random forest and Markov Random Field. "without prior" refers to the approach neglecting prior knowledge about the relative arrangement of sugar beet plants upon sowing. "sugar" refers to sugar beet plants and "weed" to weeds. In the UAV dataset, saltbush, chamomile and other weeds were differentiated. Here, "SRF" refers to the additional use of spatial relationship features.

Conclusion

Real-world issues such as N fertilization and detection of weeds in field conditions were addressed in this study. Autonomous, robotic solutions acting on different scales can help improving variable rate applications and site specific treatments in the future. This study showed that a precise, autonomous detection of weeds is possible and that optimization of N fertilization in the interest of an optimal product quality and a reduced export into the environment is achievable with autonomous machinery.

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