Towards automatic UAV data interpretation for precision farming

Johannes Pfeifer [a], Raghav Khanna [b], Dragos Constantin[c], Marija Popovic [b], Enric Galceran [b], Norbert Kirchgessner [a], Achim Walter [a], Roland Siegwart [b], Frank Liebisch [a,*]

[a] Crop Science Lab, Department of Environmental Systems Science, Institute of Agricultural Sciences, Federal Institute of Technology Zürich (ETHZ), Switzerland

[b] Autonomous Systems Lab, Department of Mechanical and Process Engineering, Federal Institute of Technology Zürich (ETHZ), Switzerland

[c] Gamaya, Lausanne, Switzerland

[*] Corresponding author. Email: frank.liebisch@usys.ethz.ch

Abstract

Background: The EU-project Flourish intends to establish an autonomously operating precision farming system based on the interaction between unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs). For effective mission planning and site-specific ground intervention by the UGV, the growth, mineral nutrition, weed, and health status of the crop field must be evaluated efficiently. In this regard, the survey capabilities of UAVs can substantially leverage the economic performance and ecological sustainability of precision farming systems.

Methods: Our approach is based on 'sufficient performance ranges' (SPRs), which represent the expected optimal performance of phenotypic traits such as spectral indicators and growth parameters like canopy cover and crop height. Together with *a priori* data, such as weather situation and soil fertility maps, the UAV derived maps allow for the detection of deviations from sufficient crop development. Detected deviations are interpreted using decision tree models. Our models encompass upstream and downstream decisions necessary for scheduling site-specific and efficient ground interventions during the whole management sequence of a growing season, such as fertilizer input or weed control.

Results: This contribution presents initial results for field monitoring via UAVs. The performance of our approach is supported by ground truth data, such as crop height, canopy cover and spectral indices from sugar beets collected in 2015. Effects of variable soil fertility, weed pressure and drought stress are presented.

Conclusion: The initial results support the proposed intention to derive appropriate management decisions for stabilizing crop yield and quality while minimizing farm inputs.

Keywords: automated crop management, decision support, multispectral camera, UAV, UGV, 3D reconstruction

1. Introduction

Autonomous precision farming systems equipped with state-of the-art sensor technology and sophisticated analysis pipelines promise to provide solutions for many aspects of modern crop production. These envisaged benefits embrace more efficient resource inputs (including fertilizers, pesticides, fuel and labor), protection of the biotic and abiotic environment (such as avoidance of soil compaction), maintenance of yields and control of harvest quality. The central aim of the Flourish project (homepage: http://www.flourish-project.eu/) is developing an autonomously operating precision farming system, consisting of an unmanned ground vehicle (UGV) and an unmanned aerial vehicle (UAV). Both, UGV- and UAV derived data are used to evaluate the growth performance and status of the crop as well as weed infestation in the field site-specifically and non-destructively in order to derive management recommendations. The UGV will also be able to conduct crop management tasks such as mechanical or chemical weed control.

In this context, UAVs can provide information to support and optimize the crop management. For example, the optimal timing, location and duration of UGV missions can be identified using previous UAV surveys. Moreover, using UAVs the amounts and composition of pesticides and fertilizers to be applied can be determined before the UGV drives to the field. Last but not least, diseases and drought events could be detected in order to enable early and efficient intervention.

The EU-project Flourish started in March 2015. Seven European partner institutions are involved, covering work packages from robot design and machine vision to crop production. In this work, our basic concept for automatic UAV data interpretation is presented and three examples are chosen to demonstrate the achieved growth performance parameters: plant height, canopy cover and growth performance estimation by use of spectral indicators.

The basic concept of Flourish consists in extracting quantitative data from the UAV (and UGV) imagery and comparing the present plant trait values with existing knowledge about the optimal performance of the crop cultivar growing in a given region. This empirical knowledge will be bundled in mathematical functions (hereafter called 'sufficient performance ranges', SPRs) describing the optimal development of a specific phenotypic trait as related to thermal time. Using the SPRs, deviations from the optimal performance can be detected.

The next step of the pipeline consists of the integration of the SPRs into a framework of decision trees. The decision trees are envisaged to encompass relevant upstream and downstream decisions necessary for planning the field management during the whole growing season. The upstream planning contains scheduling of UAV measurements and collection of complementary *a priori* data (e.g. weather data, soil maps). Consequently, the program indicates which sensors and spectral indicators are ideally needed on the UAV at a specific period during the growing season. This pre-planning will significantly increase the efficiency and thus decrease computation time needed for image processing and data analysis. For downstream decision making the core function of the decision trees is the online analysis and interpretation of the data (combining different parameters and indicators) and subsequent indication of management recommendations. To give an example: among other applications the product types and amounts of herbicides in the mix for spraying the field could be calculated based on the UAV data. In this way, at the next passage of the UGV, only the needed amount of herbicide stock is brought to the field and it is not necessary to spread the remnant on the field, as it is common practice. This procedure saves herbicides, fuel and money while decreasing the risk of environmental pollution.

In order to establish an appropriate basis for data interpretation in Flourish, various data from controlled field experiments have been collected by the UAV, by manual ground truth measurements, the UGV and the ETH Zürich Field Phenotyping Platform FIP (Kirchgessner et al. under review). These data originate mostly from digital imaging performed with different sensors, such as RGB-, NDVI-, thermo- or multispectral cameras. These images need to be processed in order to extract quantitative crop information and interpreted to derive management decisions from an agronomic perspective. The latter field of activity is the topic of this paper. Here we report preliminary results of ground truth and UAV derived crop parameters, their relationship and occurrence in the field as related to specific stresses. The main aim of the 2015 campaign was recording a high variability of sugar beet performance under a real field situation.

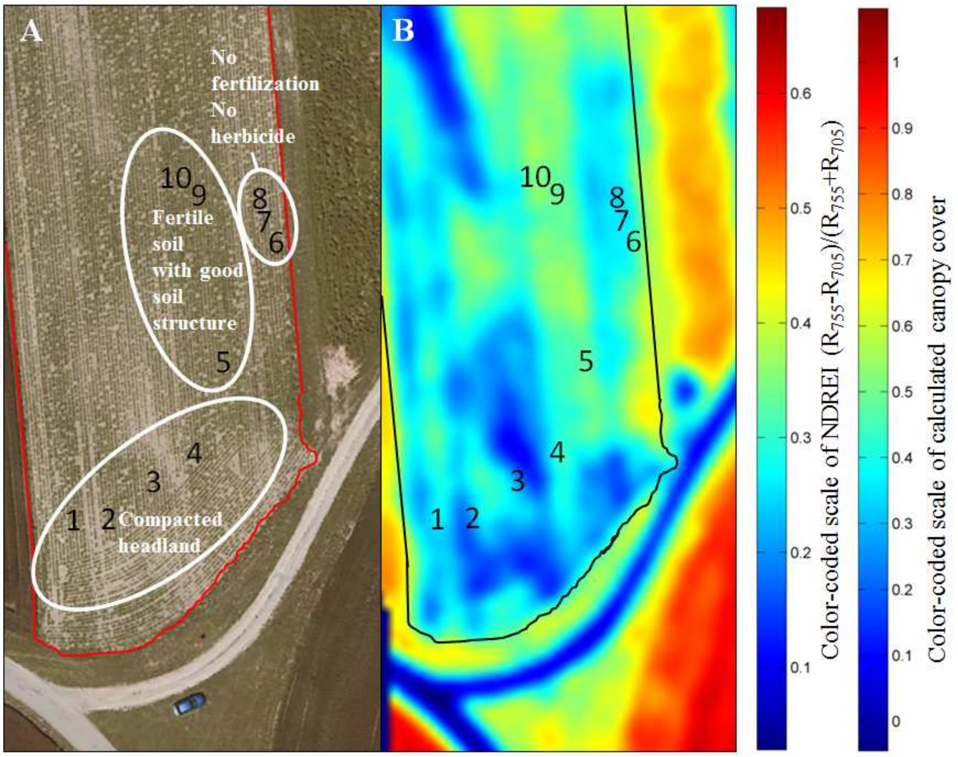

Figure 1. RGB image of the field site (field border indicated by red line) and plot locations (A) and color-coded map of NDREI index (field border indicated by black line) and estimated canopy cover (B), both taken with multispectral camera (Gamaya, Lausanne, Switzerland) on 11.06.2015. In (A), numbers show locations of plots (1 - 10) with different N and herbicide input, growth performance and weed pressure that were chosen in the field to cover a high field variation. In (B) the spatial resolution was downscaled to pixels of 1x1 m, as similar maps can be used for UGV intervention planning. Manually measured canopy cover and NDREI index of the plots was significantly (R^2=0.904, p<0.01) correlated.

2. Materials and Methods

To provide a first data set for calibration and interpretation, plant growth, development and performance on a conventional sugar beet field near Zürich (ETH research station Lindau-Eschikon, Switzerland, 47.447 N, 8.688 E, 550 m.a.s.l.; Fig. 1A) has been monitored exemplarily during the growth period 2015 using field phenotyping methods and UAV equipment. The soil type is a skeleton rich gleyic cambisol with 21% clay, 21% silt and 5% organic matter.

2.1 Ground truth and UAV measurements in the field.

Field phenotyping refers to precise methods typically used for crop phenotyping at plot level (one or few m^2). Such data acquisition is typically performed by either manual image acquisition using common or modified commercially available DSLR cameras mounted on tripods (RGB, GBNIR, Grieder et al. 2015), or by handheld devices (ASD, SPAD, LAI, yardstick-measurements of maximum plant height, as described by Liebisch et al. (2014) and Constantin et al. (2015), or by visual scoring such as BBCH, weed cover, leaf area affected by pests and diseases. Devices used for ground truth measurements and specifications are listed in Table 1. Aerial data was collected using a low cost UAV platform (DJI Phantom) carrying a high resolution (11 Megapixel) GoPro Hero® 2 camera (GoPro, Inc, USA) or a Sony FDR-X1000V with a wide angle (fisheye-) lens (Sony, Tokio, Japan). The UAV based multispectral imaging, performed on the 11.06.2015, and pre-processing was performed by Dragos Constantin (Gamaya, Lausanne, Switzerland) using a 1 x 16 band VIS 470-650nm range and 1 x 25 band NIR 600-900nm range snapshot CMOS sensor OXI VNIR-40d (Gamaya, Lausanne, Switzerland) from a IRIS+ drone (3DR, US). Multispectral image analysis was performed using MATLAB (Kirchgessner et al. under review) and R (R Core Team 2015). Selected spectral indicators used in this work are given in Table 2.

For the field campaign ten plots, each with a size of 1.5 × 1.5 m, were distributed in the field (Fig. 1A), including both, locations with suboptimal growth performance assumingly caused by high soil density due to headland (plots 1, 2, 3 and 4), high weed pressure (no herbicide application, plots 6, 7 and 8), or low nitrogen input (no N fertilized, plots 6, 7 and 8), and vigorous growth and favorable soil conditions (plots 5, 9 and 10). In the following plots 5, 9 and 10 will be named “favorable”, plots 1, 2, 3 and 4 “headland” and plots 6, 7 and 8 “no N no herbicide”. All plots were treated with fungicides according to common practice, thus effects of fungal diseases were negligible. Manual measurements were done weekly for GBNIR (NDVI) and RGB, SPAD (n=10 youngest fully developed leaves per plot), LAI, yardstick-measurements of maximum plant height (n=10 per plot), BBCH (n=10 plants per plot), scoring of weed cover, scoring of leaf area affected by pests and diseases and monthly for ASD field spectrometer measurements. Specific calibration experiments like determination of leaf chlorophyll content were conducted as necessary. On 29.09.2015 a number of nine beets per plot were harvested and yield and quality parameters were determined for three representative beets. From the end of June 2015 a pronounced drought period led to significant effects visible in many ground truth parameters.

Height estimation from UAV images (by Sony FDR-X1000V camera) was achieved according to the protocol provided by Khanna et al. (2015). Canopy cover was measured by image segmentation using either custom made scripts based on MATLAB or a machine vision algorithm based on a set of training images (Guo et al. 2013).

2.2 Sufficient performance ranges

As a reference data base for data interpretation, the ground truth data were expressed as mathematical functions (SPRs). Using these functions, deviations from the optimal performance can be detected automatically at a given time during the growing season. Crop growth mainly depends on field management and abiotic, such as temperature and water availability, or biotic factors, such as disease occurrence. For this reason the ground truth parameters reflecting specific components of growth were plotted (Fig. 2), according to Milford et al. (1985), over thermal time (accumulated temperature above 3°C). Plots 9 and 10 showed significantly higher yields compared to the other plots and were therefore chosen as reference plots for a first iteration of the SPRs. The data basis needs to be refined and adjusted if other cultivars and soil types are to be interpreted.

2.3 Decision trees

To parameterize the superordinate program for scheduling UAV and UGV missions (Fig 3A), *a priori* data will be used additionally to current UAV derived data inputs. Clearance for UGV missions in the field however does not solely depend on demand, but also trafficability of the soil, in order to prevent soil compaction. For clearance of UAV missions the thermal time after sowing is a very important base. For example, at a thermal time of 50°C (in 2015 this was about 12 days after sowing), weeds may emerge. Weed emergence is a very important parameter, as the efficiency and therefore also the environmental impact of herbicide application significantly depends on optimal timing. Consequently, the superordinate program will command a first UAV mission for weed detection after thermal time 50°C. If multispectral indices (such as NDVI) exceed a certain threshold reporting “more vegetation than expected due to SPR”, flight altitude will be decreased in a follow up flight mission in order to schedule a more detailed weed classification subprogram, “weed module” (Fig. 3B).

With respect to site-specific N fertilization, from thermal time 120°C (in 2015 this was about 26 days after sowing) a first nitrogen fertilization could be reasonable, depending on N availability on the field. Therefore, from 120°C a UAV mission for the determination of N nutrition status will be released and the subprogram “N demand module” started (Fig. 3C). The time window for the subordinate program “N demand module” may be adjusted according to *a priori* data on soil fertility or N min value.

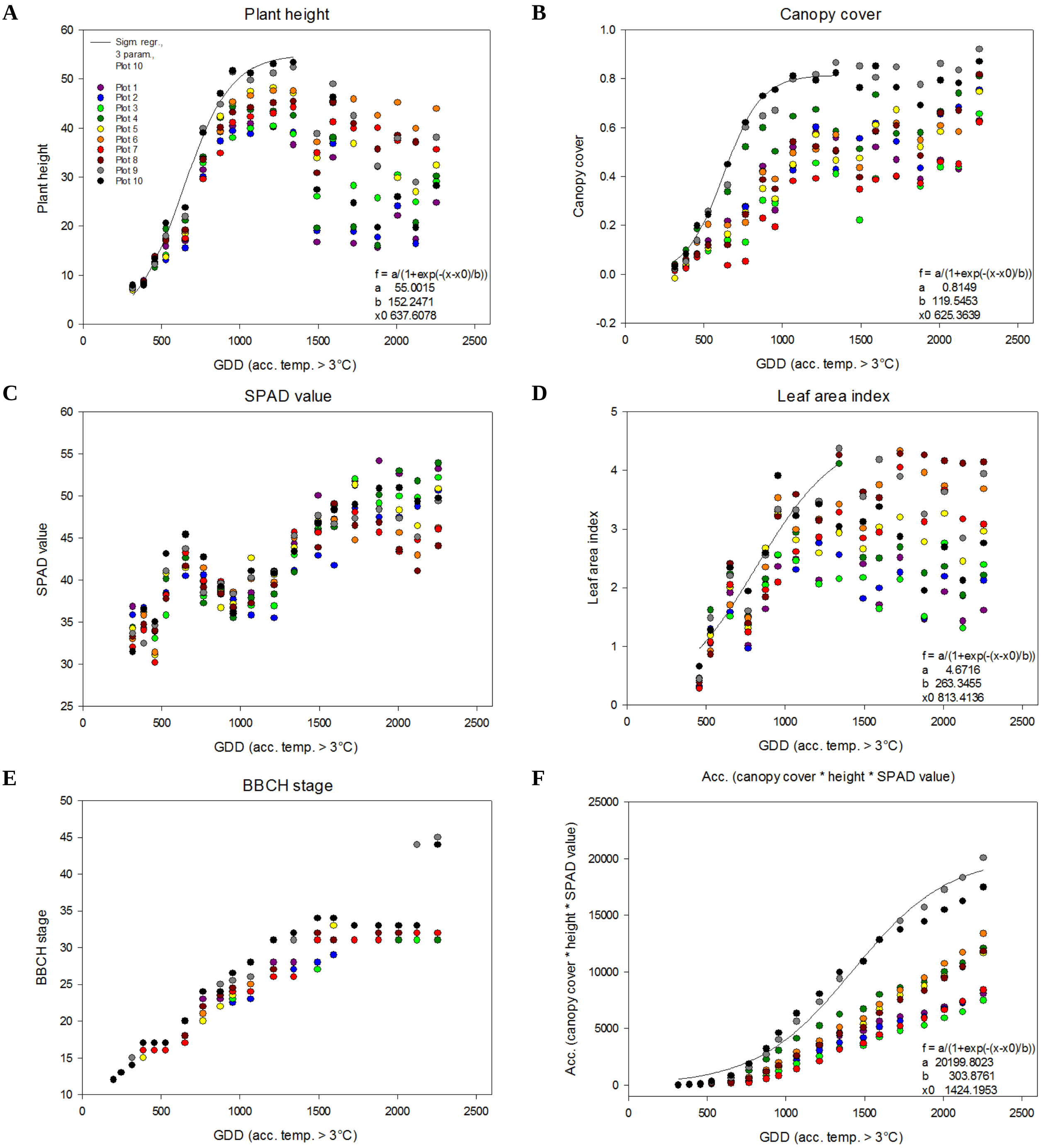

Figure 2. Sufficient performance ranges (SPRs) derived for plant height (A), canopy cover (B), SPAD value (C), leaf area index (D), BBCH (E) and a combination of canopy cover*height*SPAD value (F). A sigmoidal regression model with 3 parameters was used in the first iteration of SPR construction for all data except BBCH and SPAD. Data after 1500 GDD was excluded from the SPR construction because a drought event took place, which was visible in all data. Please note for example bad wilting recovery of plots 1 to 4 in (A), which were growing in compacted headland, after 1700 GDD, when other plots recovered after precipitation events.

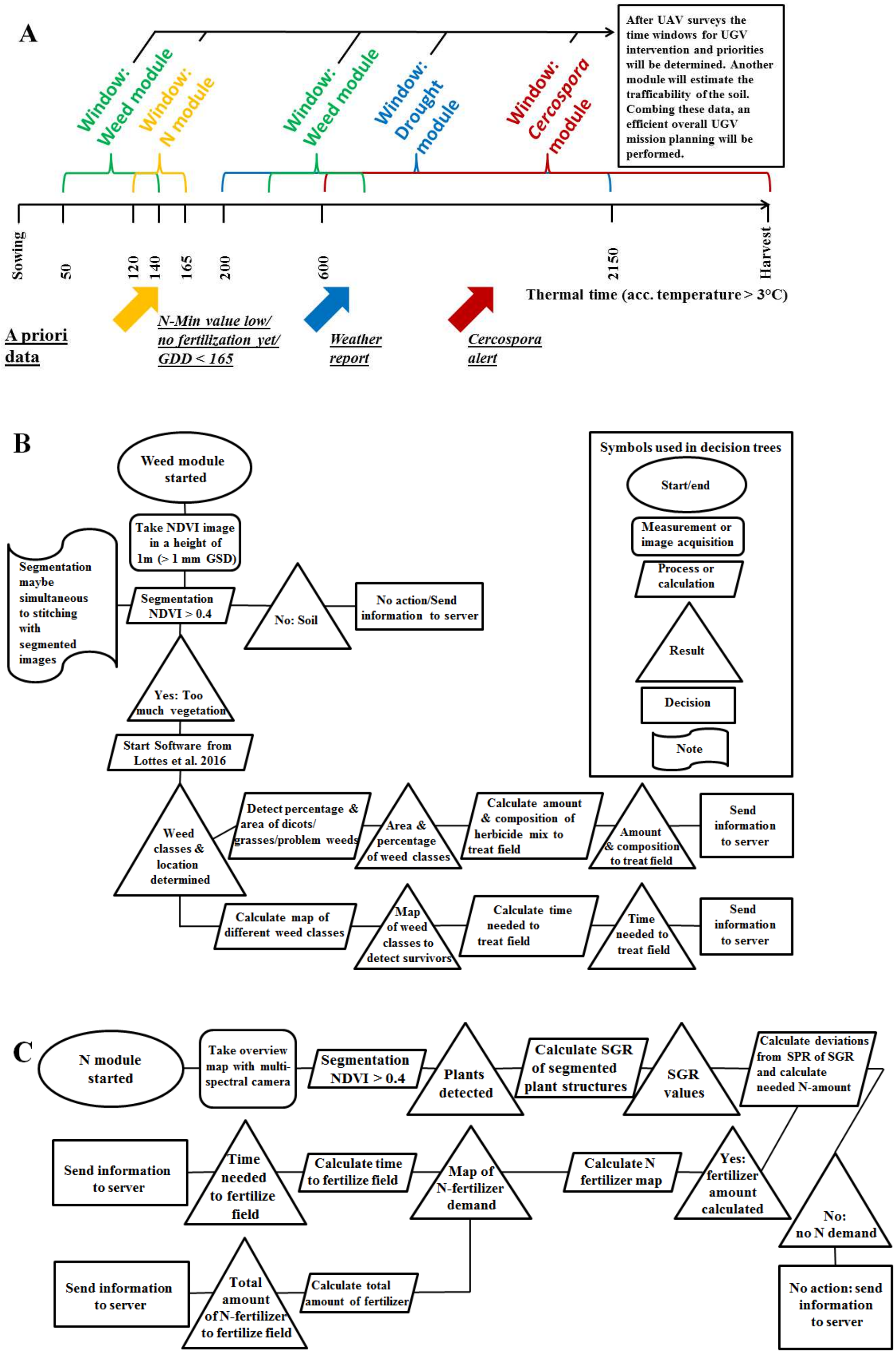

Figure 3. Concept of decision trees: superordinate program scheduling UAV missions (upscale) according to time windows defined by thermal time and *a priori* data (A), and examples for subordinate modules “weed module” (B) and “N-demand module” (C) that will be started according to superordinate program (downscale). In (C) the spectral indicator SGR (sum of 500-599 nm) was chosen, as this indicator was highly correlated to nitrogen content of leaves at a thermal time of 955 GDD (67 days after sowing).

Table 1. Specification of devices and methods used for collection of ground truth parameters.

Parameter, crop trait	Name of device	Supplier	Reference
NDVI value and canopy cover	XNiteCanon450NDVI - Canon Rebel 450D 12.2 MPx Vegetative Stress Camera	LDP LLC, USA	Liebisch et al. 2015 Grieder et al. 2015
RGB image	EOS digital 550 D, 18 MPx, Canon; combined with a 18 - 55 mm EFS lens, Canon, Japan	Canon, Japan	N.A.
Leaf area index	LAI-2200 Plant Canopy Analyzer	LI-COR Inc., USA	Delegido et al. 2013
SPAD value	SPAD 502 Plus Chlorophyll Meter	Konika-Minolta Inc., Japan	Liebisch et al. 2014
Maximum crop height	Yardstick	N.A.	Anthony et al. 2014, Khanna et al. 2015, Liebisch et al. 2014
Weed cover	Visually scored	N.A.	Marx et al. 2012, Rath et al. 2012, Schuster et al. 2007
Leaf area affected by pests and diseases	Visually scored	N.A.	Mahlein et al. 2010, Mahlein et al. 2013
BBCH	Visually scored according to BBCH scale	N.A.	BBLF 2001
Reflectance spectrum	ASD Fieldspec pro 3	ASD Inc., USA	Liebisch et al. 2014

3. Results and Discussion

The different soil conditions and treatments of the studied plot locations significantly affected several yield and quality parameters (Fig. 4). Compared with plots located in the headland, plots with favorable growing conditions showed higher sugar yield (Fig. 4A), while the plots “no N no herbicide” yielded the same amount of sugar. In general, the yield potential of the field was very high and nitrogen was likely not limiting in the beginning of the growing period due to frequent fertilization with manure in recent years. Plots located in the headland showed lower fresh weight yield (Fig. 4B) and the amino-N content of these plots – amino-N and other compounds are known to reduce the sugar extractability - were significantly lower compared to the other plots (Fig. 4C). Remarkably, the sugar content (Fig. 4D) of the “no N no herbicide” plots was lowest, while the sugar content of the plots in the “headland” was highest. Most likely these results reflect not only different N availability in the soil but also different water availability of the studied locations in a year with a pronounced drought event.

Several spectral indicators extracted for plots 1 to 10, provided by the multispectral cameras on 11.06.2015, showed strong and highly significant correlations to ground truth parameters reflecting the crops′ growth performance, such as canopy cover and plant height (see Table 2). Figure 1B shows a map of the NDREI index with which the canopy cover could be satisfactorily estimated. Yet, not only with multispectral indicators but, using a method published recently by Khanna et al. (2015), also with simple RGB cameras carried by UAVs meaningful maps for important growth parameters, such as crop height can be achieved (Fig. 5B). However, for height determined with this method no significant correlation to ground truth data was achieved until now and the map shows several discrepancies likely caused by suboptimal imaging frequency and flight path and processing artefacts. We intend to improve the methodology by extending the flight duration, imaging frequency and will test upgraded navigation systems in order to improve the reconstruction.

Table 2. Spectral indicators as adapted from literature, provided by the multispectral cameras on the 11.06.2015, showed strong and highly significant correlations to ground truth parameters. Asterisks indicate significant and highly significant differences, respectively.

Phenotypic trait assessed by reflectance indicator	Reflectance indicator	Reference	Formula (adjusted to available bands according to reference)	Coefficient of correlation
Canopy cover	PMI	Mahlein et al. 2013	$(R_{525}-R_{585})/(R_{525}+R_{585})+R_{725}$	0.977**
SPAD value	SBRI	Mahlein et al. 2013	$(R_{575}-R_{515})/(R_{575}+R515)-R_{705}/2$	-0.789**
Plant height	MCARI1	Haboudane et al. 2004	$1.2*[(2.5*(R_{805}-R_{675})-1.3*(R_{805}-R_{555})]$	0.814**
Leaf area index	NDREI	Gitelson and Merzlyak 1994	$(R_{755}-R_{705})/(R_{755}+R_{705})$	0.951**
Leaf fresh weight	VARIgreen	Gitelson et al. 2002	$(R_{555}-R_{655})/(R_{555}+R_{655}-R_{475})$	0.835**
Leaf dry weight	RGR	Sims and Gamon 2002	R_{685}/R_{515}	-0.892**
Fresh weight yield	TVI	Haboudane et al. 2004	$0.5*(120*(R_{755}-R_{555})-200*(R_{675}-R_{555}))$	0.845**
Sugar yield	TVI	Haboudane et al. 2004	$0.5*(120*(R_{755}-R_{555})-200*(R_{675}-R_{555}))$	0.636*

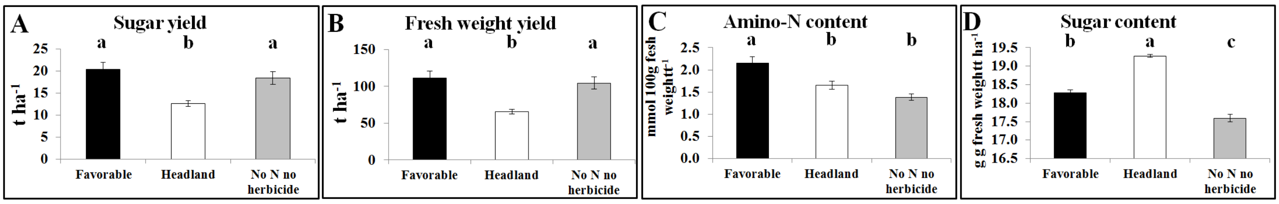

Figure 4. Yield and quality parameters (mean value ± SE; sugar yield (A), fresh weight yield (B), Amino-N content (C), sugar content (D)) were affected by the treatments ("No N no herbicide") and soil conditions ("favourable" conditions and "headland"). Statistically significant differences are indicated by different letters above bars.

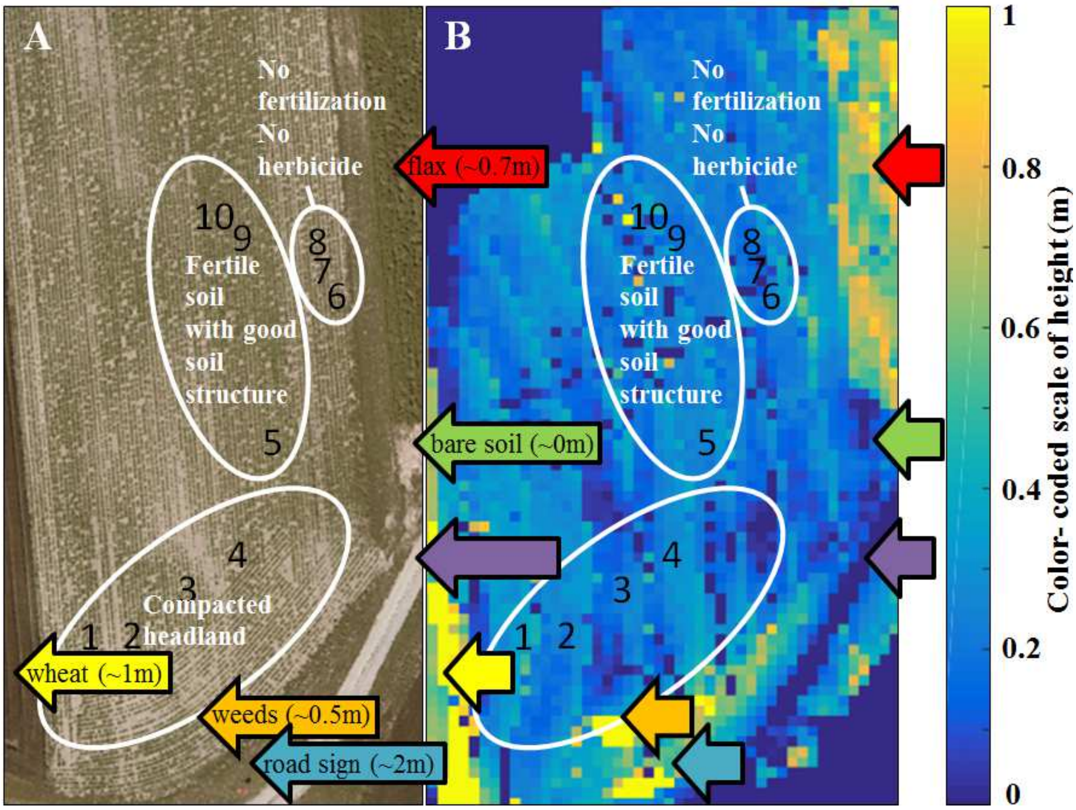

Figure 5. RGB image of the field site and plot locations (A, 11.06.2015 by Gamaya) as compared to color-coded, UAV derived map of extracted plants heights (B, 17.06.2015, by Sony FDR-X1000V camera; homogeneous blue areas in upper left and lower right corner were not sampled). In (A) numbers show locations of plots (1 - 10) with different N and herbicide input, growth performance and weed pressure that were chosen in the field to cover a high field variation. The height map (B) shows that meaningful height data can be extracted from single UAV surveys with the ground detection method developed by Khanna et al. (2015). Arrows in (A), and corresponding arrows in (B), indicate locations with characteristic and known height values for validation. The artefacts in (B), e.g. wave structure, motivate improvements to the methodology.

4. Conclusions

The results achieved in 2015 are applicable to define a first iteration of time-dependent and site-specific ranges of crop growth performance and management relevant traits. We were able to assess heterogeneity in field fertility and weed pressure and could quantify plant height, which is an interesting trait for automatic drought detection. Having more iteration from more years in this region, crop performance models based on SPRs will be derived and refined. These models can be used to classify the crop growth performance in categories, as for example "optimal performance" or "suboptimal performance – indicating that specific management actions are necessary". It is aimed that UAV derived data can be categorized and interpreted by means of decision trees. These decision trees will take advantage of several data sources, such as UAV derived data, weather data, soil maps and field history. Data interpretation should allow the deduction of crop management recommendations in the context of precision farming. By just assessing traits without any field management recommendations, slightly adapted software solutions could be used to evaluate crop breeding trials such as investigation of nitrogen use efficiency and drought tolerance.

Acknowledgements

We want to thank Ronald Vögeli, Martin Bertschi and Andreas Bertschi from the agricultural school Strickhof in Lindau-Eschikon, Switzerland for providing the experimental field, the professional field management and advice. This research was sponsored by the European Community´s framework programme Horizon 2020 under grant agreement no. 644227-Flourish.

References

Anthony D., S. Elbaum, A. Lorenz, C. Detweiler, 2014. On crop height estimation with UAVs. In *Intelligent Robots and Systems (IROS 2014), IEEE/RSJ International Conference*. Chicago, USA, September 14-18. 4805-4812. http://dx.doi.org/10.1109/IROS.2014.6943245 .

BBLF, 2001. Entwicklungsstadien mono- und dikotyler Pflanzen. Biologische Bundesanstalt für Land und Forstwirtschaft. BBCH Monografie, Germany. http://dx.doi.org/10.5073/bbch0514 .

Constantin D., M. Rehak, Y. Akhtman, F. Liebisch, 2015. Detection of crop properties by means of hyperspectral remote sensing from a micro UAV. In *21. Workshop Computer-Bildanalyse in der Landwirtschaft and 3. Workshop Unbemannte autonom fliegende Systeme (UAS) in der Landwirtschaft*. Braunschweig, Germany, May 7. Heft Nr. 88 http://www2.atb-potsdam.de/Hauptseite-deutsch/Institut/Abteilungen/Abt6/CBA/publikationen.htm .

Gitelson A.A., M.N. Merzlyak, 1994. Quantitative estimation of chlorophyll using reflectance spectra: experiments with autumn chestnut and maple leaves. Journal of Photochemistry and Photobiology (B), 22, 247 – 252. http://dx.doi.org/10.1016/1011-1344(93)06963-4 .

Gitelson, A.A., Y.J. Kaufman, R. Stark, D. Rundquist, 2002. Novel algorithms for remote estimation of vegetation fraction. Remote sensing of environment. 80, 76-87. http://dx.doi.org/10.1016/S0034-4257(01)00289-9 .

Grieder, C., A. Hund, A. Walter, 2015. Image based phenotyping during winter: a powerful tool to assess wheat genetic variation in growth response to temperature. Functional Plant Biology. Published online, http://dx.doi.org/10.1071/FP14226 .

Guo, W., U.K. Rage, S. Ninomiya, 2013. Illumination invariant segmentation of vegetation for time series wheat images based on decision tree model. Computers and Electronics in Agriculture. 96, 58-66. http://dx.doi.org/10.1016/j.compag.2013.04.010 .

Haboudane, D., J.R. Miller, E. Pattey, P.J. Zarco-Tejada, I.B. Strachnan, 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote sensing of environment. 90, 337-352. http://dx.doi.org/10.1016/j.rse.2003.12.013 .

Khanna R., M. Möller, J. Pfeifer, F. Liebisch, A. Walter, R. Siegwart, 2015. Beyond point clouds - 3D mapping and field parameter measurements using UAVs. In *Emerging Technologies & Factory Automation* (ETFA*), 2015 IEEE 20th Conference*. Luxembourg, Luxembourg, September 8-11. http://dx.doi.org/10.1109/ETFA.2015.7301583 .

Kirchgessner, N., F. Liebisch, K. Yu, J. Pfeifer, M. Friedli, A. Hund, A. Walter, under review. The ETH Field Phenotyping Platform FIP - A Cable-Suspended Multi-Sensor System.

Liebisch, F., G. Küng, A. Damm, A. Walter, 2014. Characterization of crop vitality and resource use efficiency by means of combining imaging spectroscopy based plant traits. In *Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing, IEEE International; 2014,Vol. 6*. Lausanne, Switzerland, June 24-27.

Liebisch, F., N. Kirchgessner, D. Schneider, A. Walter, A. Hund, 2015. Remote, aerial phenotyping of maize traits with a mobile multi-sensor approach. Plant Methods. 11:9. http://dx.doi.org/10.1186/s13007-015-0048-8 .

Lottes, P., M. Hoeferlin, S. Sanders, M. Mueter, P. Schulze Lammers, C. Stachniss, 2016. An Effective Classification System for Separating Sugar Beet and Weeds in Precision Farming Applications. In *Proceedings of the IEEE International Conference on Robotics & Automation (ICRA).* Stockhol, Sweden, May 19.

Mahlein, A.K., 2010. Detection, identification, and quantification of fungal diseases of sugar beet leaves using imaging and non-imaging hyperspectral techniques. Dissertation, University of Bonn, Bonn, Germany.

Mahlein, A.K., T. Rumpf, P. Welke, H.W. Dehne, L. Plümer, U. Steiner, E.C. Oerke, 2013. Development of spectral indices for detecting and identifying plant diseases. Remote Sensing of Environment .128, 21–30. http://dx.doi.org/10.1016/j.rse.2012.09.019 .

Marx, C., J. Pastrana-Peréz, M. Hustedt, S. Barcikowski, H. Haferkamp, T. Rath, 2012. Selektive Unkrautbekämpfung mittels Lasertechnik. In *25th German Conference on Weed Biology and Weed Control*. Braunschweig, Germany, March 13-15. http://dx.doi.org/10.5073/jka.2012.434.026 .

Milford, G.F.J., T.O. Pocock, J. Riley, A.B. Messem, 1985. An analysis of leaf growth in sugar beet. Annals of Applied Biology. 106(1), 187-203. http://dx.doi.org/10.1111/j.1744-7348.1985.tb03108.x .

Rath, T., J. Pastrana, 2012. Human vs Computer: Image processing to detect overlapping plants. Landtechnik. 67 (3), 172–178.

Schuster, I., H. Nordmeyer, T. Rath, 2007. Comparison of vision-based and manual weed mapping in sugar beet. Biosystems Engineering. 98(1), 17-25. http://dx.doi.org/10.1016/j.biosystemseng.2007.06.009 .

Sims, D.A., J.A. Gamon, 2002. Relationships between leaf pigment content and spectral reflectance across a wide rage of species, leaf structures and developmental stages. Remote sensing of Environment. 81, 337-354. http://dx.doi.org/10.1016/S0034-4257(02)00010-X .