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Spatial Combination of Sensor Data deriving from Mobile Platforms for Precision Farming Applications

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„ Ich höre und ich vergesse.
Ich sehe und ich erinnere mich.
Ich mache und ich verstehe.“

Konfuzius

"I hear and I forget.
I see and I remember.
I do and I understand."

Confucius

Contents

Abbreviations and Acronyms

ANOVA	Analysis of Variance
BGF	Blue-Green Fluorescence
BM	Biomass
cv	Cultivated Variety
DV	Dependent Variable
FERARI	Fluorescence Excitation Ratio Anthocyanin Relative Index
FLAV	Flavonol Index
FRF	Far-Red Fluorescence
FS	FieldSpec HandHeld, spectrometer
GPS	Global Positioning System
ha	Hectare
HS	HandySpec Field®, spectrometer
HVI	Hyperspectral Vegetation Index
IDV	Independent Variable
ISO	International Organization for Standardization, standard
IT	Inneres Täle, research field
LAI	Leaf Area Index
LW	Lammwirt, research field
MMS1	Monolithic Miniature-Spectrometer 1
MP	Multiplex® Research, fluorescence sensor
ms	Millisecond
mS	Milli-Siemens
N	Nitrogen
N_{avail}	Soil Available Nitrogen
NBI	Nitrogen Balance Index
NDVI	Normalized Difference Vegetation Index
nm	Nanometer
N_{min}	Available mineralized nitrogen
OSAVI	Optimized Soil-Adjusted Vegetation Index
PF	Precision Farming
QGIS	Quantum Geographical Information System, software
R	Reflectance
REIP	Red-Edge Inflection Point
RI	Riech, research field
RS	Remote Sensing
RTK	Real-Time Kinematic
SAVI	Soil-Adjusted Vegetation Index
SenGIS	Competence Centre for Sensors and Geoinformation Systems, research project

SF	Smart Farming
SFR	Simple Fluorescence or Chlorophyll Ratio
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle
Z	Zadoks Growth Scale

Summary

Optical sensors based on spectrometry or fluorescence are of particular interest to agriculture as they can determine multiple valuable parameters, such as the nutritional state of a plant through non-destructive methods. In combination with variable rate technologies this enables us to generate targeted decisions for a particular application, creating site-specific implementations. A site-specific fertiliser application will lead to a reduced fertilizer allocation in a field while optimising the yield. Even though there is a wide range of tasks on an agricultural farm throughout the year, optical sensors can only be used on a limited amount of them. However, their output can be significant. Passive spectrometers rely on light radiation, giving faster a gross overview of the field, whereas fluorescence sensors can be more precise, requiring a closer contact to the plant. The cost of sensors is still a limiting factor for adaptation, while there is a need for a more thorough utilisation of sensor data and relevant decision support systems.

This thesis is a first attempt to combine optical sensors on a ground and on an aerial platform for field measurements in wheat, to identify the nitrogen (N) levels, while simultaneously estimating biomass (BM) and predicting yield. The Multiplex® Research (MP) fluorescence sensor was used for the first time in wheat. The individual objectives were: (i) Evaluation of different, available sensors and sensor platforms used in Precision Farming for quantifying the crop nutrition status, (ii) Acquisition of ground and aerial sensor data with two ground spectrometers, an aerial spectrometer and a ground fluorescence sensor, (iii) Development of effective post-processing methods for correction of the sensor data, (iv) Analysis and evaluation of the sensors with regard to the mapping of biomass, yield and nitrogen content in the plant, and (v) Yield simulation as a function of different sensor signals.

The main chapters of this thesis consist of three papers, published in international peer-reviewed journals. The first publication is a comprehensive literature research on sensor platforms, and identifies current sensor platforms used in agricultural research. A general subdivision of sensors and their applications was done, based on a detailed categorisation model. It evaluates their strengths and weaknesses, and discusses research results of scientific groups using both aerial and ground platforms with different sensors. In addition, autonomous robots and swarm technologies suitable for agricultural tasks were reviewed, mainly considering factors such as low weight, availability and group interaction between individual robots. The second publication focuses on spectral and fluorescence sensors for BM, yield and N detection. The ground sensors were mounted on a mobile test carrier, the Hohenheim research sensor platform "Sensicle", allowing different mounting positions with regard to height above canopy and distance to the tramline. A further spectrometer, installed in a fixed-wing unmanned aerial vehicle (UAV), was flown over the research fields. In this study, the sensors of the Sensicle and the UAV were used to determine plant characteristics and yield of three-year field trials at the research station Ihinger Hof, Renningen (Germany), an institution of the University of Hohenheim, Stuttgart (Germany). Winter wheat (*Triticum aestivum* L.)

was sown on three research fields, with different N levels applied to each field. The frequent measurements in the field were geo-referenced and logged with an absolute GPS accuracy of $\pm$ 2.5 cm through a Real-Time Kinematics (RTK) correction signal; the GPS data of the UAV was corrected based on the pitch and roll position of the UAV at each measurement. The time and position correction of each sensor was crucial to ensure that their spatial placement was consistent with the other sensors. All measurements were assigned to the plots within the experimental field design by the GPS RTK signal. In the first step of the data analysis, raw data obtained from the sensors was post-processed with scripts, and the raw values of the wavelengths were converted into indices and ratios relating to plant characteristics. The converted data of the fluorescence sensor and the spectrometers used on the Sensicle were analysed, and the results of the correlations were interpreted related to the dependent variables (DV) BM weight, wheat yield and available N. The results showed significant positive correlations between the DV's and the Sensicle sensor data. For the third paper, the UAV sensor data was included into the evaluations. The UAV data analysis revealed low significant results for only one field during the experimental year in 2011. Based on the experience derived from this thesis, a multirotor UAV was considered as a more viable aerial platform, that allows for more precision and higher payload. Thereby, the ground sensors showed their strength at a close measuring distance to the plant and a smaller measurement footprint. Throughout paper two and three, the results of the two Sensicle spectrometers, FieldSpec HandHeld (FS) and HandySpec Field® (HS), showed significant positive correlations between yield and the indices from CropSpec, NDVI (Normalised Difference Vegetation Index) and REIP (Red-Edge Inflection Point). Also, FERARI and SFR (Simple Fluorescence Ratio) of the MP fluorescence sensor showed an Adjusted r^2 of 0.5–0.7, and were chosen for the yield prediction model analysis. With the available N, CropSpec and REIP correlated significantly with Adj. r^2 = 0.7–0.9. The biomass weight correlated with REIP even at a very early growing stage (Z 31), and with SAVI (Soil-Adjusted Vegetation Index) at ripening stage (Z 85), both with Adj. r^2 = 0.7. REIP, FERARI and SFR showed high correlations to the available N, especially in June and July. Established optical sensors for N fertilisation in practical agriculture measure the indices NDVI, CropSpec and REIP, which is why special attention was paid to them. The ratios and signals of the MP sensor are highly significant compared to the biomass weight above Z 85, with Adj. r^2 = 0.7–0.9. The evaluations successfully prove that both Sensicle spectrometers are capable of detecting the crop nutrition status in the field. They are suitable for data comparison and data combination with the MP fluorescence sensor, whose active light source can compensate for the main disadvantage of a spectrometer which is the changing light radiation during a measurement operation. Through a combination of fluorescence ratios and spectrometer indices, linear models for the prediction of wheat yield were generated, correlating significantly over the course of the vegetative period for research field Lammwirt (LW) in 2012 (Adj. r^2 = 0.5–0.8). The best model for field LW in 2012 was selected for cross-validation with the measurements of the fields Inneres Täle (IT) and Riech (RI) in 2011 and 2012. The cross-validation was not significant with the collected sensor data from these fields. However, by exchanging one spectral index with a fluorescence ratio in a similar linear model, it showed significant

correlations. The RF$_{UV}$ signal and the HVI index, combined with the CropSpec index or the FERARI ratio, should be further trained and validated in terms of wheat yield prediction. The current work successfully proves the combination of different sensor ratios and indices for the detection of plant characteristics. The aerial measurements showed that the use of a fixed-wing UAV did not provide accurate data, and that the measurement method of this system is insufficient, therefore a multirotor system for new aerial sensor missions would be preferred. The spectrometers FS and HS showed good analysis results compared to the DV's, even though the FS sensor was more reliable than the HS sensor regarding higher correlations to the DV's. Above all, the MP fluorescence sensor proved to be a universally applicable sensor, showing significant correlations to the investigated characteristics such as BM weight, wheat yield and available N. Therefore, the MP sensor can be applied successfully in new fields like detection of grain characteristics, and it can be used flexibly and independently of light radiation. Adding a sensor system infrastructure to the Sensicle, can result in easier data acquisition and further improvements in data analysis. Based on the derived experience, the measurements with the sensors parallel to each other are recommended with a sensor fusion logic. All in all, sensor technology can be used for prediction or quantification of field parameters. The combination of sensor signals offers the possibility for better and more robust predictions without employing destructive methods. Yet, more development needs to be done, to create robust systems and easy tools for the farmer.

Zusammenfassung

Optische Sensoren auf Basis von Spektrometrie oder Fluoreszenz sind für die Landwirtschaft von besonderem Interesse, da sie mittels nicht-destruktiver Verfahren wertvolle Parameter bestimmen können, wie beispielsweise den Versorgungszustand einer Pflanze. In Kombination mit teilflächenspezifischer Ausbringtechnik ermöglicht dies, gezielte Entscheidungen für eine bestimmte Anwendung zu treffen und standortspezifisch die richtige Menge zu applizieren. Eine standortspezifische Düngung führt zu einer reduzierten Düngemittelgabe auf einem Feld bei gleichzeitiger Optimierung des Ertrags. Auch wenn es auf einem landwirtschaftlichen Betrieb das ganze Jahr über ein breites Arbeitsspektrum gibt, können optische Sensoren nur in begrenztem Umfang dafür eingesetzt werden. Ihre Wirkung kann jedoch beträchtlich sein. Passive Spektrometer sind auf Lichtstrahlung angewiesen, und ermöglichen einen schnellen Überblick über die Situation im Feld, wohingegen Fluoreszenzsensoren noch präziser sein können, jedoch einen geringen Abstand zur Pflanze benötigen. Die Kosten der Sensoren sind nach wie vor ein limitierender Faktor für die Etablierung auf landwirtschaftlichen Betrieben, wobei dafür auch eine umfassendere Nutzung der Sensordaten und der relevanten Auswertesysteme erforderlich ist.

Diese Arbeit ist ein erster Versuch, optische Sensoren auf einer Sensorplattform am Boden und in der Luft bei Feldmessungen in Weizen zu kombinieren, um die Stickstoff-(N)-Werte zu identifizieren, während gleichzeitig die Biomasse (BM) geschätzt und der Ertrag vorhergesagt wird. Erstmals wurde hierfür der Fluoreszenzsensor Multiplex® Research (MP) in Weizen eingesetzt. Die Ziele dieser Dissertation umfassen: (i) Bewertung verschiedener, verfügbarer Sensoren und Sensorplattformen, die in der Präzisionslandwirtschaft zur Quantifizierung des Ernährungszustandes von Nutzpflanzen verwendet werden, (ii) Erfassung von Sensordaten mit zwei Spektrometern für Bodenanwendungen, einem Spektrometer auf einem Modellflugzeug und einem Fluoreszenzsensor am Boden, (iii) Erstellung effektiver Nachbearbeitungsmethoden für die Korrektur der Sensordaten, (iv) Analyse und Evaluation der Sensoren im Hinblick auf die Abbildung der Biomasse, des Ertrags und des Stickstoffgehaltes in der Pflanze, und (v) Ertragssimulation als Funktion von Merkmalen unterschiedlicher Sensorsignale.

Die Hauptkapitel dieser Arbeit setzen sich aus drei Artikeln zusammen, die in international begutachteten Fachzeitschriften publiziert wurden. Die erste Veröffentlichung ist eine umfassende Literaturrecherche über Sensorplattformen und identifiziert aktuelle Sensorplattformen, die in der Agrarforschung eingesetzt werden. Basierend auf einem detaillierten Kategorisierungsmodell wird eine allgemeine Unterteilung der Sensoren und deren Anwendungsgebiete vorgenommen. Es bewertet ihre Stärken und Schwächen, und diskutiert Forschungsergebnisse der wissenschaftlichen Gruppen, die diese Luft- und Bodenplattformen mit unterschiedlicher Sensorik nutzen. Darüber hinaus werden autonome Roboter und für landwirtschaftliche Aufgaben geeignete Schwarmtechnologien beschrieben, die durch ihr geringes Gewicht, ihre flexible Anzahl und der Interaktion in der Gruppe sehr gut für Arbeiten in der Landwirtschaft geeignet sind. Die zweite Publikation konzentriert sich auf Spektral-

und Fluoreszenzsensoren für die Erfassung von BM, Ertrag und N. Die Bodensensoren wurden auf einem mobilen Versuchsträger, der Hohenheimer Forschungssensorplattform „Sensicle", montiert, der unterschiedliche Montagepositionen bezüglich Höhe über dem Bestand und Abstand von der Fahrgasse ermöglicht. Ein weiteres Spektrometer war in einem Modellflieger (UAV) verbaut, der für die Befliegung der Versuchsfelder genutzt wurde. In der vorliegenden Arbeit wurden die Sensoren auf dem Sensicle und dem UAV in dreijährigen Feldversuchen auf der Versuchsstation Ihinger Hof der Universität Hohenheim in Renningen für die Bestimmung von Pflanzenmerkmalen und des Ertrags eingesetzt. Auf drei Versuchsfeldern wurde Winterweizen (*Triticum aestivum* L.) ausgesät, und in einem randomisierten Versuchsdesign unterschiedliche N-Düngestufen angelegt. Die wiederholten Messfahrten im Feld wurden mit einer absoluten GPS Genauigkeit von $\pm$ 2,5 cm mittels des Real-Time Kinematik (RTK) Korrektursignals verortet und geloggt; die GPS Daten des UAV's wurden mittels der Nick- und Rollposition lagekorrigiert. Die Zeit- und Lagekorrektur jedes Sensors ist dabei entscheidend, um deren räumliche Verortung auf den gemeinsamen Messpunkt sicherzustellen. Alle Messwerte wurden mittels des GPS RTK Signals den Parzellen innerhalb des Versuchsdesigns zugeordnet. Im ersten Schritt der Datenanalyse wurden die von den Sensoren gewonnenen Rohdaten mit Skripten nachbearbeitet, und die Rohwerte der Wellenlängen in Indizes und Ratios umgerechnet. Die Daten des Fluoreszenzsensors und der zwei am Sensicle verwendeten Spektrometer wurden analysiert, und die Ergebnisse der Korrelationen in Bezug zu den abhängigen Variablen (DV) BM-Gewicht, Weizenertrag, verfügbarer sowie aufgenommener N dargestellt. Die Ergebnisse zeigen signifikante, positive Korrelationen zwischen den DV's und den mit dem Sensicle erhobenen Sensordaten. Für die dritte Publikation wurden die Sensordaten des UAV in die Auswertungen miteinbezogen. Die Analyse der UAV Sensordaten zeigte niedrige signifikante Ergebnisse für nur ein Feld im Versuchsjahr 2011. Basierend auf den Erfahrungen aus dieser Arbeit wird ein Multikopter als zuverlässigere Luftplattform erachtet, der mehr Präzision und eine höhere Nutzlast ermöglicht. Die Sensoren auf dem Sensicle zeigten hier ihren Vorteil bedingt durch einen kürzeren Messabstand zur Pflanze und einer kleineren Messfläche. Die Ergebnisse der beiden Sensicle-Spektrometer FieldSpec HandHeld (FS) und HandySpec Field® (HS) zeigen in den Publikationen Zwei und Drei signifikante, positive Korrelationen zwischen dem Ertrag und den Indizes von CropSpec, NDVI (Normalised Difference Vegetation Index) und REIP (Red-Edge Inflection Point). Auch FERARI und SFR (Simple Fluorescence Ratio) des MP Fluoreszenzsensors weisen einen Adj. r^2 von 0,5–0,7 auf, und wurden für die Analyse des Ertragsvorhersagemodells ausgewählt. Mit dem verfügbaren N korrelierten CropSpec und REIP hochsignifikant mit Adj. r^2 = 0,7–0,9. Das BM-Gewicht korrelierte bereits ab einem sehr frühen Wachstumsstadium (Z 31) mit REIP und im Reifestadium (Z 85) mit SAVI (Soil-Adjusted Vegetation Index), jeweils mit Adj. r^2 = 0,7. REIP, FERARI und SFR zeigten hohe Korrelationen mit dem verfügbaren N, insbesondere im Juni und Juli. Auch etablierte optische Sensoren für die N-Düngung in der praktischen Landwirtschaft erfassen die Indizes NDVI, CropSpec und REIP, weshalb diesen Indizes besondere Aufmerksamkeit galt. Die Ratios und Signale des MP Sensors sind vor allem ab Z 85 gegenüber dem BM-Gewicht hochsignifikant, mit Adj. r^2 = 0,7–0,9.

Die Auswertungen belegen erfolgreich, dass beide Spektrometer auf dem Sensicle in der Lage sind, den Versorgungszustand der Pflanzen auf dem Feld zu erfassen. Sie eignen sich für den Vergleich und die Kombination von Daten mit dem MP Fluoreszenzsensor, dessen aktive Lichtquelle den Hauptnachteil eines Spektrometers, der sich ändernde Lichtstrahlung während eines Messvorgangs, kompensieren kann. Durch eine Kombination von Fluoreszenzwerten und Spektrometerindizes wurden lineare Modelle zur Vorhersage des Weizenertrags erstellt, die im Verlauf der Vegetationsperiode für das Versuchsfeld Lammwirt (LW) im Jahr 2012 signifikant korrelierten (Adj. r^2= 0,5–0,8). Das beste Modell für das Feld LW im Jahr 2012 wurde für die Kreuzvalidierung mit den Messungen der Versuchsfelder Inneres Täle (IT) und Riech (RI) in den Jahren 2011 und 2012 ausgewählt. Die Kreuzvalidierung mit den erfassten Sensordaten auf diesen Versuchsfeldern war nicht signifikant. Jedoch zeigen sich durch den Austausch nur eines Spektralindizes mit einem Fluoreszenzratio in einem ähnlichen, linearen Modell signifikante Korrelationen. Das Signal RF_{UV} und der Index HVI, kombiniert mit dem Index CropSpec oder FERARI, sollten in Bezug auf die Vorhersage des Weizenertrags weiter trainiert und validiert werden.

Die vorliegende Arbeit zeigt erfolgreich, dass sich die Kombination verschiedener Sensorwerte und Sensorindizes zur Erkennung von Pflanzenmerkmalen gut eignet. Die Versuche zeigten, dass durch den Einsatz des Modellfliegers keine ausreichend genauen Messdaten erhoben werden konnten und, dass das Messverfahren dieses Systems ungenügend ist, mit der Konsequenz des Systemwechsels hin zu einem Multikopter. Die Spektrometer FS und HS zeigten gute Analyseergebnisse im Vergleich mit den DV's, obwohl der FS-Sensor zuverlässiger war als der HS-Sensor hinsichtlich höherer Korrelationen mit den DV's. Vor allem der MP-Fluoreszenzsensor erwies sich als universell einsetzbarer Sensor, der signifikante Korrelationen zu den untersuchten Merkmalen BM-Gewicht, Weizenertrag und verfügbarem N aufzeigte. Damit kann der MP-Sensor in neuen Bereichen wie der Erfassung von Getreidemerkmalen erfolgreich eingesetzt werden, und ist flexibel und unabhängig von der Lichteinstrahlung einsetzbar. Das Hinzufügen einer System-Infrastruktur für die Sensoren am Sensicle kann zu einer einfacheren Datenerfassung und einer weiteren Verbesserung der Datenanalyse führen. Basierend auf den gewonnenen Erfahrungen werden für künftige, parallele Sensormessungen Methoden zur Fusion von Sensordaten empfohlen. Insgesamt kann die Sensorik zur Vorhersage oder Quantifizierung von Feldparametern eingesetzt werden. Die Kombination von Sensorsignalen bietet die Möglichkeit, bessere und robustere Vorhersagen ohne den Einsatz destruktiver Methoden zu treffen. Dennoch muss mehr Entwicklung betrieben werden, um robuste und einfache Systeme für den praktischen Landwirt zu schaffen.

1 Introduction

Famers are the experts of their land. Farmers know their fields and the special environmental conditions of their area. They know the spots, where water accumulates in humid periods, in which spots of the field crops are earlier affected by drought, they know how much fertiliser to apply where, ... Like this is has been for decades and still is, where farming is family owned or organised as small farm corporations. However, todays agriculture is facing a change. The size of farms and fields is growing, with larger working widths and faster application velocities. Nowadays it becomes difficult to employ sufficient skilled employees to work on a farm with modern farm equipment, farming practices and to know the fields with its special local conditions. Furthermore, legislation requires detailed reporting and record keeping of the yearly tasks, for the applied amounts and their locations. Farming without the support of technology appears like a view to ancient times.

1.1 Data Collection on Platforms

Data collection methods in agriculture have been influenced by environmental research, as agricultural investigation methods are similar. The sensors have to be close to the object by touching the crop or the soil, or the sensors measure from the distance. Important requirements for a measurement mission are the footprint, the resolution and the duration to gather all data, independent if it is a ground or an aerial sensor platform. For contact or close-by measurements, the footprint is small, and the resolution and duration are very high. To increase the duration and footprint, scientists in 1850 flew with hot air balloons to take photos of the ground. But at that time, resolution was poor. In 1920, scientist started with initial arial photography and photogrammetry from airplanes. In 1960, the term "Remote Sensing" (RS) has been described and used the first time (Campbell et al., 2011). The first satellite images had been available to science in 1995 for environmental studies (Baumann, 2009), thanks to the advances in digital image processing and hyperspectral sensors. Since then, the resolution increased rapidly, and sensors decreased in size and weight, up to a level that now model airplanes or multicopter, generally called Unmanned Aerial Vehicles (UAV) or Unmanned Aerial Systems (UAS), can lift these sensor units for data acquisition.

One of the most important sensor signals, as the basis for all localisation features, is the Global Positioning System (GPS) signal (Bossler et al., 1980). Three decades ago in the 1990s, agricultural equipment manufacturer started to integrate GPS receiver on their machines. Like that, the machine with mounted devices and sensors was enabled for geo-referenced localisation and precise data logging in the field, as a mobile platform for completion of its planned task or a simultaneous data acquisition. From this time on, the sensor technology in agriculture has been offered below the term Precision Farming (PF) solutions, opening the space for more technology and sensors towards Smart Farming (SF).

As sensors only based on a single sensor signal may lead to misinterpretation, the fusion

of information is essential. More sensors or signals provide more robustness to mobile out-door systems which are exposed to many dynamic disturbances like sunlight, dust, moisture, obstacles or shocks (e.g. Agogino et al., 1995; Åstrand et al., 2002; Griepentrog et al., 2010). Therefore combinations of sensors are preferred for modern systems (Zillmann et al., 2006), which can be set up as (1) redundant, (2) complementary or (3) cooperative sensor configurations (Durrant-Whyte, 1988).

The mobile sensor platforms used for this study were a ground vehicle and a fixed-wing UAV: on the ground a rebuilt self propelled Hege 76 multi-equipment carrier (Wintersteiger AG, Ried, Austria), the so called Hohenheim multi-sensor platform "Sensicle" (for more information and image see Keller et al. (2012) and Zecha et al. (2017); for the aerial data acquisition a modified E-Trainer 182 (Graupner GmbH & Co. KG, Kirchheim, Germany) (for more details see Link et al., 2013).

1.2 Objectives

This dissertation examines the availability of sensor platforms that are used in the different research areas. The focus is on measurements with redundant and complementary sensors mounted on a research platform, and on decision extraction for PF applications. The objectives in detail were:

- to evaluate different, available sensors and sensor platforms used in Precision Farming for quantifying the crop nutrition status,

- to acquire ground and aerial sensor data with two ground spectrometers, an aerial spectrometer and a ground fluorescence sensor,

- to develop effective post-processing methods for correction of the sensor data,

- to analyse and evaluate the sensors with regard to the mapping of biomass, yield and nitrogen content in the plant, and

- to simulate the yield as a function of different sensor signals.

1.3 Structure of the Dissertation

Section 1 introduces to the collection of data on various platforms over time. It emphasises the importance of the GPS technology and its application areas. Furthermore it names the objectives of this thesis. Section 2 reviews current sensor platforms and robots used in farming applications. It evaluates their strengths and limitations, and discusses research results of scientific groups using these aerial and ground platforms for their research. Section 3 compares fluorescence and reflectance sensor data that have been gathered with the Hohenheim research sensor platform "Sensicle". It discovers the usability of these sensors and shows the correlation results of the winter wheat (*Triticum aestivum* L.) field trials for yield, available

Nitrogen (N) and the N uptake. Section 4 analyses the spectrometer data from the UAV and the Sensicle sensor data, and does a cross-validation with the developed linear models by combining fluorescence ratios and spectrometer indices. Section 5 discusses the findings of Section 2 – Section 4, which consist of articles published in international peer-reviewed scientifc journals. In addition, it evaluates aerial and ground vehicles as mobile sensor platforms and, the combination of fluorescence and reflectance sensor data, and gives an outline for sensor systems in PF.

2 Mobile sensor platforms: categorisation and research applications in precision farming

Many sensors and sensor systems are available and can potentially be used to produce more yield with less input. Platforms on the ground and in the air offer a huge potential as carrier for sensors. Systems as a combination of sensor and platform are used in PF research since decades for mapping, scouting, monitoring and application tasks.

This publication reviews available manual, automatic and autonomous mobile sensor platforms and robots used in agricultural and related research projects. It provides an overview of ground platforms and UAV, and describes the applications where existing mobile ground and aerial sensor platforms can be applied to. A detailed categorisation for sensor platforms has been outlined by the authors, and actual ground and aerial platforms for soil and plant characteristics detection are characterised in this manuscript. It concludes with the uncertainties, strengths and limitations of the different sensor platform systems.

Depending on the technology development, labour costs and human safety requirements of each country, the technology levels of platforms will be on a different technology level. While intermediate technology platforms will use raw data and feature level fusion, high technology platforms will incorporate swarm intelligence, and combine system architecture with decision fusion and fusion algorithms. Information fusion is a necessary requisite to merge all sensor data for decision-making in agriculture. And Adamchuk et al., 2010 see PF as "a perfect field where sensor fusion concepts are essential".

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Mobile sensor platforms: categorisation and research applications in precision farming

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Abstract. The usage of mobile sensor platforms arose in research a few decades ago. Since the beginning of satellite sensing, measurement principles and analysing methods have become widely implemented for aerial and ground vehicles. Mainly in Europe, the United States and Australia, sensor platforms in precision farming are used for surveying, monitoring and scouting tasks. This review gives an overview of available sensor platforms used in recent agricultural and related research projects. A general categorisation tree for platforms is outlined in this work. Working in manual, automatic or autonomous ways, these ground platforms and unmanned aircraft systems (UAS) with an agricultural scope are presented with their sensor equipment and the possible architectural models. Thanks to advances in highly powerful electronics, smaller devices mounted on platforms have become economically feasible for many applications. Designed to work automatically or autonomously, they will be able to interact in intelligent swarms. Sensor platforms can fulfil the need for developing, testing and optimising new applications in precision farming like weed control or pest management. Furthermore, commercial suppliers of platform hardware used in sensing tasks are listed.

1 Introduction

The first stationary industrial robot was developed by George Devol and Joseph F. Engelberger in the early 1960s for the production line of an automotive manufacturer (Engelberger, 1999). Due to constant, structured and predictable environmental indoor working conditions, the control and management of them can be done in an automated way. Based on this knowledge, operational outdoor platforms emerged in research: manually driven, partly automatic, completely autonomous mobile sensor platforms or robots. Their implementation with the same safety and accuracy for field tasks is more challenging due to the rough and changing conditions. One important criteria for outdoor operations is a precise position referencing of a vehicle or robot. The civilian use of the global positioning system (GPS) and the switched off selective availability (SA) in the year 2000 by the US Department of Defence (Langley, 1997) enabled a serviceable position referencing outdoors. With differential GPS (DGPS) and the Russian Global Navigation Satellite Sys-

tem (GLONASS), accuracy increased to less than 5 m. This capability also allowed for more applications in agriculture. In the early 1990s, technologies for precision farming (PF) were introduced to the market. PF was initially used as a synonym for automatic steering systems (Auernhammer, 2001). Meanwhile the main focus of PF has shifted and the aim of current PF applications is to apply the input factors at the right time, in the right amount at the right place (Khosla, 2010). Against this background practical applicability for PF technology remains linked to high-tech agriculture using machine guidance and site-specific seeding, fertilization plant protection with variable rates of seeds, fertilizer or pesticides (Seelan et al., 2003). Efficient use of resources, protection of the environment and documentation of applied management prescriptions are the reasons for PF application (Haboudane et al., 2002). Through new developments in sensor techniques and computer electronics, their reliability increased significantly. It became easier to adapt approaches from related research fields into the practical application of PF and thus to improve management decisions in terms of nutrient

application. Nearly all manufacturers of agricultural machinery offer sensor systems for their field vehicles, subsequent data processing and subsequent application planning. Noncomparable data, conversion problems derived from various manufactures using different sources, as well as the lack of appropriate decision support systems (DSS) has impeded the full adoption of PF in the past (McBratney et al., 2005).

During the last decade, the main focus lay on development of sensors able to guide farmers through site-specific nutrient management. Most sensors are based on optical technology, e.g. interpretation of spectral signatures to identify the nutrient status in plants and to apply online directly the right amount of fertilizer. Recognized heterogeneity in fields due to differences in crop colour, yield amount or weed spots can be precisely georeferenced and considered for future management decisions (Zhang et al., 2002).

Most commercially available sensors are based on single sensor signals. In some cases, this leads to misinterpretation of the truth for variability or heterogeneity (Zillmann et al., 2006). In order to strengthen the reliability of implemented sensor signals, the idea of using a combination of sensors is gaining popularity. To merge all sensor data for analysis, the fusion of information is a necessary requisite. Dasarathy (2001) used "information fusion" as a general term for data fusion approaches. Furthermore, Adamchuk et al. (2010) described PF as "a perfect field where sensor fusion concepts are essential". The integration of multiple sensors for decision-making in agriculture is already utilised by researchers and developers; however, costs of sensor systems have to decrease for a faster adoption on farm sites (Adamchuk et al., 2010). Implementing low-cost consumer (e.g. digital cameras) or industrial components (e.g. robust software routines for feature recognition) will enable farmers to economically gain access to this sensing technology.

This paper aims to cover three questions: (1) How can mobile sensor platforms be categorised in general? (2) Which mobile sensor platforms are already in use or in development? (3) For what tasks are existing mobile sensor platforms able to be applied to?

In this publication an overview will be given about available manual, automatic and autonomous mobile sensor platforms used in actual agricultural and closely related science projects. Section 2 presents a general categorisation for mobile sensor platforms used for data collection. Furthermore, Sect. 2 focuses on architecture models implementing fusion algorithms on actual platforms and robots fulfilling these requisites. Section 3 delves into detail regarding the sensor platforms used in agricultural research topics. Ground and aerial vehicles for detection of soil and plant characteristics are described and an outlook to robot swarms will be given. Section 4 discusses uncertainties, strengths and limitations of the presented sensor systems. This literature overview is concluded by Sect. 5.

2 Platform categorisation

The term "platform" has multiple meanings. This paper focuses on the technological term where it is defined as a "carrier system for payload, as a combination of hardware and software architecture frameworks" (Merriam-Webster Inc., 2013) e.g. "the combination of a particular computer and a particular operating system" (Princeton University, 2013). Several categories of platforms can be differentiated as displayed in Fig. 1. The particular modules are described below in the following text.

2.1 Research area

Innovations in mobile sensor platforms for PF originate from various research areas. Amongst them, the military sector, with a high capital backing. Therefore, highly advanced solutions can be achieved quickly. With a certain time delay, the civil sector also benefits from these developments. Most technology first applied in military operations spills over to the civil sector, e.g. GPS, internet or satellite imagery. Most clients of this new technology are from industry and the surveying business, having sold a high number of units. Even though aquaculture for food production increases every year, with huge application areas, agriculture and forestry have increasing demands for technology, e.g. for weed management, but these markets are slow to emerge (Frost et al., 1996; McBratney et al., 2005).

2.2 Systematic concept

The systematic concepts include a range of tasks and consist of mapping, monitoring, scouting and applying. The different research areas require diverse systematic concepts. The military mainly needs applications for scouting tasks to observe terrain and make tactical decisions. In the area of agriculture, at the moment, monitoring and scouting sensor platforms are mainly being implemented (Griepentrog et al., 2010; Ruckelshausen, 2012).

2.3 Approach

The systematic concept defines whether the approach must be online or if an offline strategy would be sufficient for the special task. An offline (mapping) method is based on stored data. It is characterized by separate steps: (1) measurement/detection, (2) calculation, and (3) application (Ruckelshausen, 2012) and provides the possibility to combine different sources of information (Maidl et al., 2004; Link et al., 2007). An online (sensor) method takes into account the measured data in real time for the decision calculation. This is done by a task controller, a terminal or a computer system and is considered directly for the on-the-go application. In combination with DGPS the data of the application can be mapped for data analysis and traceability. Due to the
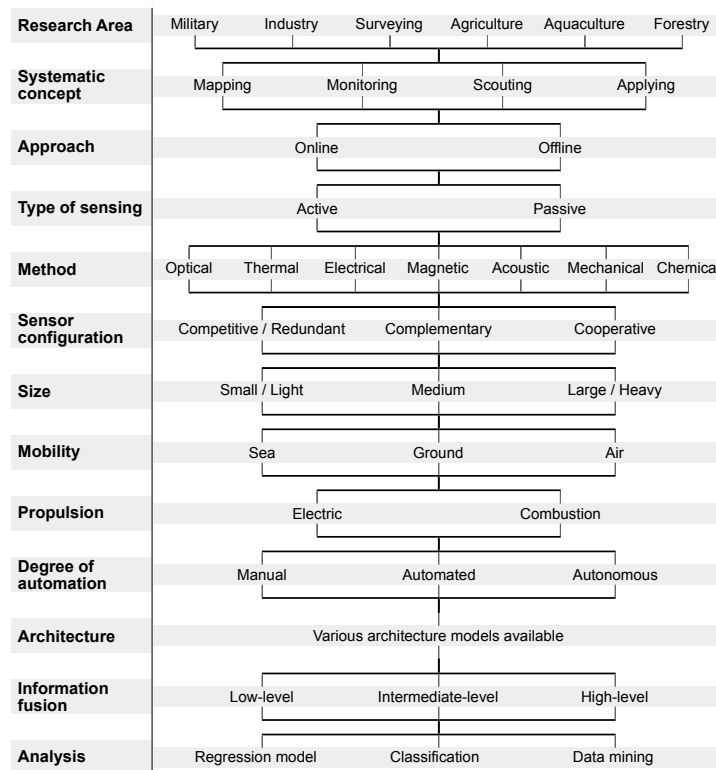
Figure 1. A general platform categorisation tree (according to Compton et al., 2013).

availability of new sensor and information system technologies, offline techniques can be replaced by online methods (Fender et al., 2006). So far, mainly online technology is implemented in practical agriculture. However, current and future concepts include the combination of online and offline approaches, so-called mapping-overlay approaches (Auernhammer, 2001).

2.4 Type of sensing

The technology differs between active and passive sensor methods. Passive sensors are dependent on ambient light conditions. They use principles of solar radiation to measure or image the energy remission of the sighted object. Active sensors provide their own illumination source and are able to obtain measurements regardless of time, day or season (Hoge et al., 1986). Nowadays, mainly active sensors with their own laser- or LED-light source are preferable. Increased measurement time and sensor operations, due to independence of natural sunlight, are the advantages of such systems.

2.5 Methods of sensing

In the area of agriculture, at the moment mainly spectrometers are implemented (Maidl et al., 2004). Also, electrical sensor systems, e.g. for soil electrical resistivity or electromagnetic induction, are used to explain soil heterogeneity in fields (Corwin and Lesch, 2003; Knappenberger and Köller, 2011). Other sensor principles, e.g. mechanical feelers, are used for machine guidance in row crops (Reid et al., 2000). A challenging research task is achieving high detection accuracy with chemical sensors. Marrazzo et al. (2005) tested intact apples and their extracted juice. The authors sought to detect similarities with an electronic nose in laboratory conditions. However, outdoor applications with the same system set-up and detection accuracy will be challenging to adapt. Zarco-Tejada et al. (2012) have been working for some years in the topic of detecting water stress with thermal sensors on an aerial platform. Registering the echoes reflected by the ground or plant surface, Andújar et al. (2011) implemented an ultrasonic sensor for weed discrimination.

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2.6 Sensor configuration

Durrant-Whyte (1988) specified three types of sensor configuration: (1) a competitive or redundant, (2) a complementary, and (3) a cooperative sensor configuration.

Competitive or redundant configurations stands for two or more sensors which supply information of the same parameter at the same location and the same degrees of freedom. It serves for increased accuracy and high reliability of the whole sensor system configuration.

Two or more sensors supplying different information about the same parameters at the same location and in different degrees of freedom are called complementary sensors. As there is no direct dependency of the sensors in a complementary configuration, it completes the information of the measurement situation.

The cooperative sensor configuration consists of independent sensors which rely on another for information. It offers emerging views on situations (Elmenreich, 2002).

2.7 Size

Depending on the efforts, incorporating multiple sensors to one system, the sensor configuration type impacts on the final costs as well as the required size and final weight of the platform. The size of a mobile sensor platform is directly correlated with the possible payload, thus on small mobile sensor platforms only light sensors can be implemented. The bigger the vehicle, the more requisites need to be fulfilled due to federal regulations or ambient claims. Also, due to technological development, platform sizes have become smaller and smaller, down to hummingbird size with only 19 g and a small video camera (AeroVironment Inc., 2013).

2.8 Mobility

Using a vehicle or a mobile platform for data acquisition offers the possibility of automation or autonomy of a system, and, compared to manual data sampling, more ground coverage is possible. Process routines can be adapted on the mobile system via an architecture model, for merging data, increased analysis speed and less operator fatigue or failures. Data transmission is linked to a server and enables live views of the acquired data. In case of measurement errors, the operator is able to react immediately, repeating the data acquisition or changing the adjustments due to an easier system overview. The decisions and necessities of a project affect the mobility of the operated platform, which will be explained in detail in the following.

2.8.1 Sea vehicles

Aquaculture is facing the situation of a continuously growing fish consumption. Fish farms benefit from research done in marine applications to reduce stress on the fish and for better observation of fish cages (Frost et al., 1996). While Frost

et al. (1996) published results about a prototype of a Remotely Operated Vehicle (ROV), He et al. (2011) showed an example for a navigation method of an Autonomous Underwater Vehicle (AUV). Osterloh et al. (2012) advanced in that research by explaining AUV systems operating in swarms. At the web page for AUV (http://www.transit-port.net), Zimmer (2013) offers recent information about the whole range of submarine vehicle applications.

2.8.2 Self-propelled ground vehicles

Ground vehicles have the advantage of high-resolution sensing and less disturbance factors (Reyniers et al., 2004). Their benefit is the ability to carrying higher loads and more equipment than it would be possible by manual hand sampling. Combustion engines are coupled with the battery and therefore they are able to offer a mobile power supply for electric sensor devices. The mission planning is more flexible compared to sensing with full-scale aircrafts and it is less sensitive to ambient weather conditions. Their disadvantages are lower surface coverage and the influence on traction and trafficability due to different terrain types or obstacles (Hague et al., 2000). In the automotive sector projects with autonomous cars are quite advanced (e.g. "Google Car" – Google Inc. & Stanford University, CA, USA or "Leonie" – Volkswagen & Technical University of Braunschweig, Germany) (Moore and Lu, 2011; Saust et al., 2011). Within the Carolo-Cup event, German student groups are requested to develop the best possible guidance for an autonomous vehicle in different scenarios like obstacle avoidance (Maurer, 2013). On the web portal http://www.therobotreport.com, Tobe (2013) informs about educational institutions, research facilities and labs working in robotics and publishes continuously other related news in this area. More details about special ground carrier systems for agricultural usage will be given in Sect. 3.1.

2.8.3 Remote and aerial platforms

After the successful start of powerful ballistic missiles, satellites in the orbit have been used for a wide range of applications, like navigation, weather research, telecommunications or environmental monitoring (Richharia, 1999). For agricultural scope, the spectral properties of the vegetation are important (Tucker and Sellers, 1986). Images provided by satellites are a common source for analysing larger regions or fields in order to detect crop health, nutrient supply, weed patches or the general crop condition (Tucker and Sellers, 1986; Moran et al., 1997; Pinter et al., 2007; López-Granados, 2011; Bernardes et al., 2012). However, the limits often lie in the low spatial resolution of these images or cloud covers in the images. For small-scale areas of interest, e.g. field trials in agriculture, higher data resolution needs to be gathered in order to have a better detection precision in the surveyed area. Firstly, the usage of manned full-scale

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Table 1. Categorisation and definitions of unmanned aircraft systems (based on Allen et al., 2011). MTOW = maximum take off weight.

UAS Category	Acronym	Altitude [m]	Endurance [h]	MTOW [kg]
Nano Aerial Vehicle	NAV	100	< 1	< 0.025
Micro Aerial Vehicle	MAV	250	1	< 5
Mini Aerial Vehicle	MAV	150[a]–300[b]	< 2	< 30 (150[a])
Close Range	CR	3000	2–4	150
Short Range	SR	3000	3–6	200
Medium Range	MR	5000	6–10	1250
Medium Range Endurance	MRE	8000	10–18	1250
Low Altitude Deep Penetration	LADP	50–9000	0.5–1	350
Low Altitude Long Endurance	LALE	3000	> 24	< 30
Medium Altitude Long Endurance	MALE	14 000	24–48	1500
High Altitude Long Endurance	HALE	20 000	24–48	(4500[c]) 12 000

[a] in Japan, [b] depending on national legislation, [c] Predator B.

aircrafts arose, which could be planned with more flexibility and much faster than satellites. Furthermore, they offer to carry most equipment loads. The mission costs are, however, disadvantageous. Within the last few years, the idea of using Unmanned Aerial Vehicles (UAV), i.e. unmanned aircraft systems (UAS) became popular. Their advantages are flexible use and inexpensive implementation without pilots on board. As for ground vehicles, several UAV competitions for students are arranged, e.g. the International Aerial Robotics Competition (IARC), with two parallel venues in Grand Forks, ND, USA and in Beijing, China, the UAV Challenge – Outback Rescue held in Kingaroy, QLD, Australia or the UAV Student Competition in Ottawa, Ontario, Canada with different types of aerial vehicles and customised sensors.

According to TheUAV (2013), "UAVs can be a remote controlled aircraft (e.g. flown by a pilot at a ground control station) or can fly autonomously based on pre-programmed flight plans or more complex dynamic automation systems". Advanced UAV can be equipped with built-in control and guidance systems to perform speed and flight path stabilization, as well as waypoint following, but they are not autonomous at all (TheUAV, 2013). The Civil Aviation Authority (CAA) defines a UAS as "individual 'System Elements' consisting of the unmanned aircraft (UA) and any other System Elements necessary to enable flight, such as a Remote Pilot Station, Communication Link and Launch and Recovery Element", whereas UAV is a legacy term and obsolete (CAA, 2012). Therefore, in the following, the term UAS will be used for describing aerial platforms.

Especially in the military sector, UAS are also named drones. Balloons and kites are excluded from this term. An important objective for UAS will be to operate without human intervention across all flight sectors (CAA, 2012). Besides the two terms UAV and UAS, many others are in use, like the vertical take off and landing (VTOL) system for copters (Watts et al., 2012), as well as remotely operated aircraft (ROA), remotely piloted vehicle (RPV) or unmanned

aircraft vehicle system (UAVS) (IDGA, 2013; FAA, 2013; ICAO, 2011). The International Civil Aviation Organization (ICAO), an agency of the United Nations, started to use the term remotely piloted aircraft system (RPAS) instead of UAS (Allen et al., 2011).

Right now, there are still a lot of different terms in use which might cause confusion. The ICAO from Canada, the CAA from the UK, the Institute for Defence & Government Advancement (IDGA), the Federal Aviation Administration (FAA) from the USA, as well as many other institutions like Eurocontrol from Belgium, the European Aviation Safety Agency (EASA) from Germany or the European Organization for Civil Aviation Equipment (EUROCAE) from France are working in the topics of definitions, standards and safety, concerning unmanned aircrafts (UA). In their publications further information is given, e.g. in ICAO Circular 328, CAP 722, or WG 73.

Watts et al. (2012) described classification terms for aerial vehicles depending on their flight time endurance, size and flight altitude following existing military descriptions. The officially used terms are summarised in Table 1 based on Allen et al. (2011), which are all referring to unmanned aircraft systems.

National regulations are however different everywhere and the discussion about safety and privacy has arisen. Only for private use in Germany, § 16 LuftVO permits a maximum take off weight (MTOW) of 5 kg for starting and landing everywhere. All other usages, independent of their MTOW, require a special permission due to federal regulations (BMJ, 2012). In the United Kingdom, according to §§ 166, 167, 253 ANO2009, no registration for an aircraft below 20 kg is needed, but an operating permission and an appropriate pilot qualification is required (CAA, 2009). The FAA in the USA restricts the usage of UAS to a maximum of 122 m (400 feet) above ground level and sufficient distance to populated areas and full-scale aircrafts. For business purposes a Special Airworthiness Certificate-Experimental Category (SAC-EC) is required additionally (FAA, 2013).

Table 2. Different types of UAS categorised into different propulsion and wing types.

Electric-Combustion/Jet-turbine	
Fixed Wing	Rotary Wing
Wing aircraft	Helicopter
Flying/Delta wing	Multicopter

Within the last decade platform sizes have become smaller and smaller since starting with RS data acquisition. As an example for aerial platforms, the decrease was from (1) satellites, to (2) full-scale aircraft. Nowadays, (3) multicopter are used more frequently, and the actual smallest aerial vehicle is the size of a (4) hummingbird. Increasing in relevance to research projects is the micro aerial vehicle (MTOW ≤ 5 kg) and mini aerial vehicle (MTOW < 30 kg). In recent years, an important focus of research groups was on the implementation of helicopters and microcopters. A variety of terrains makes their usage highly flexible and adaptable to many different tasks. Specific groups working in the field of UAS for research are presented in Sect. 3.2. Beside wind and rotor air vehicles, flapping wing UAS, e.g. from the Dutch company Green X (Enschede, Netherlands) or the "SmartBird" from the German company Festo (Esslingen, Germany), are currently in developmental focus. Another milestone with flapping wing technology is a nano UAS, the "Nano Hummingbird", by the US company AeroVironment, Inc. (Monrovia, CA, USA). This UAS has a wingspan of 16 cm, a TOW of only 19 g, and is equipped with a small colour video camera (AeroVironment Inc., 2013).

2.9 Propulsion

Depending on the time duration for each campaign or the power requirement of the whole system, the propulsion type for the mobile sensor platform needs to be selected. The energy supply for a platform with the auxiliary equipment is a fundamental criterion. UAS propulsion can be further differentiated by several criteria (see Table 2). While on the ground, electric and piston-driven vehicles are common; in aerial applications, turbine propulsion has also been developed. Installations on ground platforms can have hybrid systems installed, i.e. where a combustion engine powers the gear drive, and an alternator charges the battery. As combustion engines cause higher levels of vibration, electric drives are implemented mainly on small aerial platforms. On larger aerial platforms (> 10 kg), combustion engines are necessary to ensure higher flight time endurance and more range. The energy supply for a platform with the auxiliary equipment is a fundamental criterion.

2.10 Degree of automation

Manual applications require much supervision. Errors can happen with increasing numbers of working hours, causing lower repeatability accuracy. The more complex the process, the more possible sources for errors are given. Therefore, process automation was enforced in many areas to reduce human errors and improve quality and quantity. The more independent the degree of automation, the more complex the whole system is. "Automated" and "autonomous", are terms that have to be differentiated.

Automation in general means "the application of machines to tasks once performed by human beings or, increasingly, to tasks that would otherwise be impossible" (Encyclopaedia Britannica, 2013). Reasons for process automation are improved and uniform quality, increased performance, reduction of process costs and relief of human burden of heavy physical or monotonous work (Schuler, 1994). While automation rules can have many dependencies, interactions and linkings, a system failure would need to be resolved by a system specialist.

Autonomy covers the concepts of freedom from intervention, oversight or control of an operator or another system for decision making (e.g. Evans et al., 1992; Barber and Martin, 2001), and has a more comprehensive meaning of independence of control with learning, development and reacting processes (Smithers, 1997; Pfeifer and Scheier, 2001).

Automated and autonomous systems can substitute the most trivial working routines, are able to reduce labour costs and are not dependent on restrictions regarding the number of hours in a working day. If automated or autonomous technology are to be available on the market, easy-to-use controls are necessary. The operator needs to have a system that is easily adjustable and manageable whilst an architecture behind regulates the necessary system modifications. A remote service support, in combination with an online diagnostic tool (e.g. realised with telemetry systems), could be a solution to merge both needs. The main reason for the implementation of autonomous instead of manual or automatic systems is their ability to react. This is fundamental for control processes. Autonomous systems are capable to detect obstacles and to react immediately, i.e. they can move around and avoid a collision. Automated systems have serious problems if an obstacle appears (e.g. Crowley, 1985).

2.11 Software architecture

According to Orebäck and Christensen (2003), the most efficient strategy for designing autonomous systems or robots is the implementation of a software architecture. Moreover, Nebot et al. (2011) explained the importance of a controlling architecture in order to run a mobile sensor platform with a higher degree of automation. As the most important part of a robotic system, it has to allow coordination and cooperation between the different system elements. "The right

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Table 3. Architecture models for field robots, sorted by year of publication. Latest information 5 April 2013.

Architecture model		Author	Year
Blackboard control	–	Hayes-Roth	1985
Saphira	–	Konolige et al.	1997
TeamBots	Team robots	Balch	2013
BERRA	Behaviour-based Robot Research Architecture	Lindström et al.	2000
Umbra	"Shadow" (lat.)	Gottlieb et al.	2001
CARMEN	Carnegie Mellon Navigation	Montemerlo et al.	2003
MARIE	Mobile and Autonomous RoboticsIntegration Environment	Côté et al.	2006
ORCA	Organic Robotic Control Architecture	Makarenko et al.	2006
AGROAMARA	Agricultural Autonomous Multi-Agent Architecture Robot	García-Pérez et al.	2008
ROS	Robot Operating System	Quigley et al.	2009
MRDS	Microsoft Robotics Developer Studio	Cepeda et al.	2010
AGRITURE	AGRIcultural architecTURE	Nebot et al.	2011
FroboMind	Field Robot Architecture	Jensen et al.	2012

choice of the architecture can facilitate the specification, implementation and validation of the applications implemented for the system" (Nebot et al., 2011). Robot architecture has been developed with having in mind principles such as scalability, code reuse, abstraction hardware and data distribution (Nebot et al., 2011). "Having a universal system, modularity, openness, extendibility and simplicity are important assets" (Orebäck, 2004). Makarenko et al. (2006) proposed that a "successful framework for a robot should be (1) open source, (2) distributed under a license which allows use in commercial applications, (3) modular, and (4) distributed with a repository of tested and documented modules."

A comparison among different contemporary architectures for robots is shown and evaluated by Nebot et al. (2011). The authors discussed architectures for the field of cooperative robot systems (see Sect. 2.6 Sensor configuration). A summary list of architecture models of robots and platforms is given in Table 3. One of the first systems for the problem-solving process of artificial intelligence was the blackboard control architecture. It consists of three major components: (1) software specialist modules, (2) a blackboard like a dynamic library, and (3) a control shell. The control unit acts as a gatekeeper to determine which independent computational modules could communicate to the blackboard at what time (Hayes-Roth, 1985). Orebäck and Christensen (2003) studied more recent results by describing three architectures: (1) Saphira, (2) TeamBots, and (3) BERRA. Saphira (Konolige et al., 1997) is a robot control system with integrated routines for sonar sensor interpretation, map-building and navigation. The system TeamBots by Balch (2013) was used for single- and multi-agent mobile robotics while BERRA (Behaviour based Robot Research Architecture) (Lindström et al., 2000), the most complex system of these three, was designed for goals of scalability and flexibility (Orebäck and Christensen, 2003). The aim of their study was to give an overview of existing architectures. Finally, they proposed a generic design for a new robot architecture.

The framework Umbra enables the generation of models and simulations for intelligent system development, analysis, experimentation and control. Umbra supports the analysis of complex robotic systems and bridges between low-level engineering and constructive-level scenario simulation environments (Gottlieb et al., 2001). It is a commercial product of Sandia National Laboratories (Albuquerque, NM, USA). Another product they offer is also used for robots; the so-called SMART, the Sandia Modular Architecture for Robotics and Teleoperation. CARMEN is an open-source robot control toolkit and was created for ease of use, robustness and extensibility. It was designed as a modular software architecture with modules containing localisation, collision detection, navigation, and hardware management and communication (Montemerlo et al., 2003). The open-source framework ORCA is a component-based robotic systems for developing purposes, released under LGPL and GPL (GNU (Lesser) General Public License) licenses. It provides the means for defining and developing the building blocks, which can be pieced together to form arbitrarily complex robotic systems. For development and integration of new and already existing robotic software, the framework MARIE (Mobile and Autonomous Robotics Integration Environment) was designed (Makarenko et al., 2006). García-Pérez et al. (2008) designed an agent of behaviour architecture named AGROA-MARA, for autonomous navigation of a mobile robot. This multi-agent architecture was implemented on an articulated tractor and offers a methodological framework for farming operations, perception and control algorithms. The Robot Operating System (ROS) was developed in 2007 by Stanford University, USA. "ROS encourages well-defined data flows through ROS-topics and has become popular in recent robot projects due to its open-source BSD (Berkeley Software Distribution) license and good online documentation" (Quigley et al., 2009). Cepeda et al. (2010) presented the Microsoft Robotics Developer Studio where they tested speech recognition, vision and sensor-based navigation. The MRDS

environment was programmed for robot control and simulation and allows for the achievement of complex behaviours for a wide variety of robot hardware. AGRITURE was designed for implementation of a control system on a team of mobile robots in agricultural environments. It can interact with real and simulated devices, which is useful for optimizing the whole system (Nebot et al., 2011). FroboMind, based on ROS, is a conceptual architecture for a robot control system. It is open-source and designed for field robotics research. The concept was recently presented at the CIGR-AgEng 2012 conference by Jensen et al. (2012).

2.12   Information fusion

The terminology used to describe fusion systems is used in a wide and diverse variety of ways in the literature. In technical publications, the terms "sensor fusion", "data fusion", "information fusion", "multi-sensor data fusion" or "multi-sensor integration" refer to different techniques, technologies, systems or applications with gathered data from multiple information sources (Rothman and Denton, 1991). "Dasarathy (2001) decided to use the term 'information fusion' as the overall term for fusion of any kind of data" (Elmenreich, 2002). An exact definition of information fusion is given by the International Society of Information Fusion (ISIF): "Synergistic integration of information from different sources about the behaviour of a particular system, to support decisions and actions relating to the system." Elmenreich (2002) introduces sensor fusion as the "Combining of sensory data, or data derived from sensory data, from disparate sources such that the resulting information is in some sense better than would be possible when these sources were used individually."

Basically all creatures do sensory and information fusion. Each in their own way, they combine the impressions of different senses with learned knowledge, experience and messages from living environment (Elmenreich, 2002). Regardless of their terminology, sensor fusion techniques all benefit from (1) robust performance, (2) extended spatial and temporal coverage, (3) increased confidence, (4) reduced ambiguity and uncertainty, (5) improved resolution, (6) improved system reliability, (7) robustness against interference, and (8) increased dimensionality (Bossé et al., 1996; Grossmann, 1998).

Based on Dasarathy (1997), fusion approaches can be categorised by a three-level model: (1) low-level fusion or raw data fusion, (2) intermediate-level fusion or feature-level fusion, and (3) high-level fusion or decision fusion. "Low-level fusion or raw data fusion combines several sources of raw data to produce new data that is expected to be more informative than the inputs" (Elmenreich, 2002). Intermediate-level fusion or feature level fusion fuses features like lines, edges, textures or positions from various data sources into a new feature map for increased information content (Elmenreich, 2002). "High-level fusion or decision fusion combines deci-

sions from several experts. Methods of decision fusion include voting, fuzzy-logic, and statistical methods" (Elmenreich, 2002).

Fusion algorithms can be classified into four methods of (1) estimation, (2) classification, (3) inference, and (4) artificial intelligence. Configured in the modules of robot architecture, the fusion of information is a necessary step for data analysis and decision making. For autonomous vehicle navigation, data fusion is used, e.g. for visual target tracking (Luo et al., 2002; Jia et al., 2008).

2.13   Data analysis

The analysis of data is an essential part for coming to decisions and making applications. The analysis process consists of several parts. First, the generated data need to be controlled. For manual postprocessing a convenient data editor is necessary. The next step involves cleaning the data from irregularities or wrong information. Afterwards, the corrected data must be transformed to special file formats in order to analyse it with software programs for modelling. Several regression models are developed to analyse data. Classification algorithms are used widely for image analysis and fusion approaches. In addition to algorithm methods for classification tasks, data mining, (knowledge discovery) can be applied, but is still a rather unexplored process.

There are basically two uses of sensors on platforms; navigation sensors and mission sensors. An important principle, implemented to autonomous vehicles or robots, is the simultaneous localisation and mapping (SLAM), fusing navigation and mission sensor data. Different sensor types are used in such a system to acquire data from the environment. With this data, the analysis algorithms are defining the exact location of the vehicle and keeping its track (e.g. Durrant-Whyte and Bailey, 2006; Blanco et al., 2009).

3   Sensor platforms in agriculture

With the availability of satellite data for civil use, the analysis of spectral reflectance characteristics of plant canopies started in the late 1970s (Tucker, 1980; Tucker and Sellers, 1986). Since remote sensing (RS) research is an investigation topic with many scientists involved, the developed methods for detecting and classifying objects are advanced and used in many applications, e.g. in archaeology, geoinformatics, geophysics, land surveying, mining or agriculture. Lamb (2000) named three essentials for an RS system: (1) provide cost-effective data, (2) be capable of acquiring and providing information in a timely manner, and (3) have user-defined spectral characteristics to allow for adjusting of specific crop indicators (Lebourgeois et al., 2008).

All efforts done in agricultural research have to serve this goal: growing more and better output with less input and with less environmental impact. Sensor platforms can help to reach this goal by monitoring crop status and applying the

Table 4. Robotic ground vehicles in research as possible platforms for agricultural scopes. The described robots are mainly from European research projects and private companies. Robot names are linked to more information. Latest information 7 May 2013.

Robot name	Task(s)	Institution
AROCO	Obstacle detection, Digital Elevation Map	National Research Institute of Science and Technology for Environment and Agriculture (CEMAGREF) & LASMEA, Aubiere, France.
Large scale unmanned tractor	Modular system	Department of Automation and Systems Technology, Aalto University, Espoo, Finland.
Nuntius	Modular system	Dorhout, D., Dorhout R&D LLC, Iowa, USA.
Neobotix	Modular system	Neobotix GmbH, Heilbronn, Germany.
Grizzly, Husky	Modular systems	Clearpath Robotics Inc., Kitchener, ON, Canada.
Prospero	Modular system	Dorhout, D., Dorhout R&D LLC, Iowa, USA.
Robosoft	Modular system	Robosoft SA, Bidart, France.
Volksbot	Modular system	Fraunhofer IAIS, Sankt Augustin, Germany.

right amount of nutrients or pest controls, but actually, more work needs to be invested. Mostly, single sensor approaches on vehicles are used in combination with true ground sample data as reliable reference.

3.1 Ground vehicles

In the early 1970s, researchers had already taken advantage of ground vehicles for RS data collection (Al-Abbas et al., 1972). Since this time, an increasing number of sensor platforms and robots have been developed. The web portal for Agricultural Robotics (http://www.unibots.com) gives a general informative overview. Several robots used in research projects for agricultural purposes are described. The web page lists finished, as well as ongoing, agricultural robot projects and their managed tasks (Blackmore, 2013). Growing numbers of new projects show their strong relevance in today's agriculture due to high prices of resources and increased demand of organically grown food, as well as fast advances in technology. Sensor platforms and robots in agricultural usage are still part of research topics at universities, some of them in collaboration with industry partners (Blackmore, 2013; Tobe, 2013). Most recent robotic vehicles, as listed in Table 4, can provide a possible basis for future RS platforms in agriculture. Table 5 gives an overview of the robotic ground vehicles equipped with RS equipment mainly from European research projects.

In the following, applications implemented on ground platforms will be described with the approaches being used and their focus on crop and soil characteristics.

3.1.1 Platforms for gathering soil data

Site-specific information about soil, which provides information about yield limiting factors, can be used to derive management zones within a heterogeneous field and thus provide the possibility to apply input factors based on the existing demand (Fraisse et al., 2001; Mzuku et al., 2005). Sensors that operate close to the soil surface are not affected by

weather and field surface conditions, but only a few sensors are commercially available for on-the-go measurement of soil properties (Adamchuk et al., 2004). Taylor et al. (2006) presented experiences and results for soil-property sensing on a multi-sensor platform. Mounted on a John Deere tractor, Sibley et al. (2008) implemented a soil nitrate mapping system, which showed the same accuracy in the field as in the laboratory. Dabas et al. (2000) used a sensor to measure the electrical resistivity in soil. As a further step, a sensor system for soil sensing, integrating electrical conductivity and pH mapping on a tractor-implement combination, has been investigated by Jonjak (2011), where fields were mapped with online sensing technology, as well as systematic grid sampling. Adamchuk et al. (2010) explained fusion approaches for soil and crop data and their importance. The running European project OPTIFERT is aiming at the realisation of a sensor platform for georeferenced measuring of different soil ions to allow precision fertilisation (Doyle et al., 2013).

3.1.2 Platforms for plant characteristics

Plant characteristics such as biomass, leaf area index or nutrient status provide information about the current status of the plants, which hints at growing conditions within the field. Faster detection and analysis methods for plant characteristics can support the reduction of lots of manual work for data acquisition. In plant breeding this is still a necessary step. Plant phenotyping like in the German project BreedVision can help to attain precise results in plant-breeding processes. Morphological and spectral information in crops with low density, e.g. corn, are measured and automatically fused together. This is done with a light-curtain, spectrometer, RGB (Red Green Blue) camera, 3-D-Time-of-flight cameras and a distance sensor (Busemeyer et al., 2010). The fluorescence sensor, Multiplex® (Force-A, Orsay, France), used at the University of Hohenheim, Stuttgart, Germany showed good correlations to nitrogen status and yield in winter wheat (Martinon et al., 2011). Stabilizing algorithms for video cameras can be integrated for inter-row navigation and

Table 5. Ground platforms equipped with remote sensing equipment for agricultural purposes. Robot names are linked to more information. Latest information 7 May 2013.

Robot name	Task(s)	Institution
Armadillo Scout	Obstacle detection, scouting, 3-D-mapping, weeding	Griepentrog, H. W. et al., Department for Instrumentation and Test Engineering, University of Hohenheim, Stuttgart, Germany, University of Southern Denmark, Odense, Denmark and KU-LIFE, University of Copenhagen, Denmark.
ASuBot	Obstacle detection, weeding	Jensen, K. et al., Institute of Chem-, Bio- and Environmental Technology, University of Southern Denmark, Odense, Denmark and Aarhus University, Denmark.
BoniRob	Plant phenotyping	Ruckelshausen, A. et al., University of Applied Sciences, Osnabrück, Germany and Amazonen-Werke H. Dreyer GmbH & Co. KG, Hasbergen, Germany.
BreedVision	Plant phenotyping	Ruckelshausen, A. et al., University of Applied Sciences, Osnabrück, Germany, Amazonen-Werke H. Dreyer GmbH & Co. KG, Hasbergen, Germany and State Plant Breeding Institute, University of Hohenheim, Stuttgart, Germany.
DEDALO	Obstacle detection, detection and classification of objects	García-Alegre, M. C. et al., Centre for Automation and Robotics, Spanish National Research Council & Systems Engineering and Automation Department, Carlos III University of Madrid, Spain.
Hako	Obstacle detection, mowing, precision seeding, hoeing, spraying	Griepentrog, H. W. et al., Department for Instrumentation and Test Engineering, University of Hohenheim, Stuttgart, Germany and KU-LIFE, University of Copenhagen, Denmark.
HortiBot	Row detection and spraying	Melander, B., Aarhus University, Denmark and Research Centre Flakkebjerg, Slagelse, Denmark.
Robotic arm	Plant care & nutrition, fruit harvesting	Johnson, L. and Dyar, S., Massachusetts Institute of Technology (MIT), Cambridge, MA, USA.
Sensicle	Weed detection, crop nitrogen status	Claupein, W., Gerhards, R., et al., University of Hohenheim, Stuttgart, Germany.
Volksbot RT-3 mod	Plant detection & mapping	Weiss, U. and Biber, P., Robert Bosch GmbH, Schwieberdingen, Germany.
Weedcer	Image analysis, spraying	Berge, T. W. et al., Norwegian Institute for Agricultural and Environmental Research (Bioforsk), Ås, Norway, Adigo Ltd., Oppegård, Norway and SINTEF Information and Communication Technology, Oslo, Norway.
Zero2Nine	Obstacle & row detection	Linz, A., Ruckelshausen, A., et al., University of Applied Sciences, Osnabrück, Germany.

field-mapping even if the terrain causes lots of vehicle vibrations (Sainz-Costa et al., 2011). Recognizing contextual information of crop rows by the use of machine vision on a platform was first tested in the early 1990s. The methods of steering a weeding tool within a few centimetres beside a plant were taken, enhanced and commercialised by Tillett and Hague (1999) and the Danish Institute of Agricultural Sciences (Søgaard and Olsen, 2003; Pedersen et al., 2006). With new software advances and algorithms for analysis, imaging devices are in use by many research groups. Other topics dealt with plant stress caused by diseases like powdery mildew (Bravo et al., 2004; Gröll et al., 2007) or take-all disease (Graeff et al., 2006). Shiratsuchi et al. (2009) used crop canopy reflectance and temperature sensing for nitrogen or water stress detection in combination with an ultrasonic sensor for crop height assessment.

3.1.3 Platforms for plant protection

Mobile sensor platforms were also implemented for plant protection. Slaughter et al. (2008) reviewed weed control systems on autonomous robots. The robots' biggest challenge remains detecting and identifying weeds under various agricultural conditions seen all over the world. Steiner et al. (2008) discussed innovative approaches in the area of remote and near range sensors used in site-specific plant protection. López-Granados (2011) recently reviewed the advances, limitations and opportunities of real-time and mapping approaches for discriminating weeds at early or late phenological stages for site-specific weed management in cropping systems. Several other projects are working on weed control approaches (Lee et al., 1999; Ruckelshausen et al., 2006; Weis, 2010), as weeds can be significantly reduced by using decision rules with modern sensor and application technologies (Gutjahr and Gerhards, 2010). Andújar et al. (2011) described an ultrasonic sensor approach for automatic discrimination between broad-leaved weeds and grasses based on

plant height with a high detection success. Due to recognized resistances of crops to chemicals and decreasing numbers of available active chemical substances, advances in mechanical weeding are more relevant than ever. The challenge is to remove weeds in all three locations: (1) inter-row, (2) intra-row, and (3) close-to-crop (Nørremark et al., 2011). For inter-row weeding, commercial solutions are already available, and intra-row applications are in development (Jørgensen et al., 2007; Kam et al., 2009; Fischer, 2012). Recently, Slaughter et al. (2012) presented an intra-row weed control system for mechanical plant protection with a hoe in order to remove weeds growing between tomato plants. In order not to damage the plant during the application, they documented each position of the sown tomato seeds with RTK accuracy. The ongoing RHEA (Robot Fleets for Highly Effective Agriculture and Forestry Management) project (http://www.rhea-project.eu), was launched in September 2010, and its' goal is the reduction of chemicals in agriculture through the use of automated ground and aerial systems. An autonomous tractor could be used for mechanical and thermal weed control (RHEA, 2013).

In "Autonomous Systems for Plant Protection", Griepentrog et al. (2010) described vehicles for monitoring, scouting and applying tasks, still being scaled to a research-based level of use. The main application for this group of robots will be firstly scouting and monitoring, including more advanced concepts in agricultural automation, such as the application of herbicides or autonomous mechanical weeding. The authors came to the conclusion that in countries with high product quality standards, high safety and environmental concerns, as well as high labour costs, robots allow economic cost reductions. Increased operational efficiencies and avoidance of negative environmental impacts are also positive effects of their use.

3.2 Unmanned Aerial Systems

UAS are already used in many research groups (Eisenbeiss et al., 2011; Herbst, 2012; Zhang and Kovacs, 2012). Due to their low price, low weight and flexible use, they are a popular tool for economical RS data acquisition. These aerial systems are promising tools to gather data in a shorter time than by a ground-based field vehicle, and in a cheaper way than it would be possible using a satellite or full-scale aircraft. UAS equipped with digital cameras are used for obtaining data, e.g. to create Digital Elevation Models (DEM) or Digital Terrain Models (DTM) for land surveying purposes (Turner et al., 2012) or for monitoring soil erosion (d'Oleire Oltmanns et al., 2012). Due to weight issues for enhanced flight time, only small GPS receivers with low accuracy are used on small UAS (Bláha et al., 2012).

Several projects with UAS used in agriculture are listed in Table 6 with payload capacity (PL), maximum take off weight (MTOW) and sensor configuration on the vehicles. Many other universities are working with UAS in non-military fields, e.g. the University of Stuttgart, Germany (Kittmann et al., 2011), the ETH Zurich, Switzerland (Bäni, 2011), the Bochum University of Applied Sciences, Germany (Bäumker et al., 2012) or the Delft University of Technology, Netherlands (de Croon et al., 2012). The Autonomous Vehicle Group at Aalborg University, Aalborg, Denmark is focusing on autonomous helicopters. Their research is broad and reaches from slung load flight, flights in turbulent wind conditions, wind power meteorology but also to applications with multispectral cameras, localization in swarms or monitoring the Arctic environment (la Cour-Harbo, 2013).

Due to the fact that an increasing number of scientists are working with these kind of planes and copters, Table 7 lists main commercial vendors for MAVs in rotary and fixed-wing configurations as an information source for aerial data acquisition projects in future.

3.2.1 UAS for plant characteristics

Within the last 5 yr UAS were also implemented into the agricultural research to gather information about plant characteristics and quality. Franke et al. (2008), in collaboration with the German Aerospace Center (DLR, Cologne, Germany), detected powdery mildew in wheat with the airborne Hyperspectral Mapper (Spectra Vista Corp., NY, USA). Two hand-held spectrometers and an airborne hyperspectral camera were compared by Øvergaard et al. (2010) for predicting grain yield and quality in spring wheat. At the University of Hohenheim, Germany, aerial reflectance measurements are conducted with a digital RGB camera (Optio10, Pentax Ricoh Imaging Co. Ltd., Tokyo, Japan) and a spectrometer device (tec5 AG, Oberursel, Germany) (Link-Dolezal et al., 2010, 2012). Lelong et al. (2008) showed that the quality of spectral ranges reached by standard digital cameras is suitable for RS, and that data preprocessing is quite effective. Hunt Jr. et al. (2010) used a filter for red light on several digital cameras without a near infrared (NIR) blocking filter on a UAS. With these calibrated cameras, they conducted good correlations at 210 m between green normalized difference vegetation index (gNDVI) and leaf area index (LAI). Also, Rabatel et al. (2012) used a single standard digital RGB camera for aerial field imaging at low altitude. They replaced the internal NIR blocking filter by a low-pass filter set. This method is a promising approach for a low-cost aerial sensor system. In southern countries, a very hot and dry summer is driving the need for irrigation. Better distribution of water can be achieved by early detection of plant stress due to water insufficiency. Therefore, Zarco-Tejada et al. (2012) used a UAS from QuantaLab IAS – CSIC, Córdoba, Spain, equipped with a thermal and a hyperspectral camera. Their results showed that crown temperature and chlorophyll fluorescence were the best indicators for water stress detection. However, fluorescence techniques within agricultural sensing platforms are still today barely in use due to the need

Table 6. Recent UAS (research) projects with agricultural background (Eisenbeiss et al., 2011). PL = Payload, MTOW = maximum take off weight, RGB = Red Green Blue, NIR = Near infrared. Project names are linked to more information. Latest information 7 May 2013.

Project name	Institution	PL [kg]	MTOW [kg]	Sensors
Fixed wing				
AggieAir	Utah State University, Logan, UT, USA	1.36	3.62	RGB + NIR camera
Altimum 3e	L'Avion Jaune, Montferrier-sur-Lèz, France	4	15	RGB + multi-spectral camera
ARTINO	Fraunhofer FHR, Wachtberg, Germany	5.4	25	Radar
Carolo 200	Technical University of Braunschweig, Germany	1.0	4–6	RGB + Video camera, Meteoro-logical measurement unit
Carolo P330	Technical University of Braunschweig, Germany	2.5	15–25	Multi-spectral + thermal camera
S GIS	University of Hohenheim, Stuttgart, Germany	1.8	4.2	Spectrometer, RGB camera
Stuttgarter Adler	University of Stuttgart, Stuttgart, Germany	5.0	25	Spectrometer, RGB + thermal camera
Rotary Wing/Multicopter				
Agricopter	Humboldt University of Berlin, Berlin, Germany	–	–	RGB + NIR camera
UAV-RS	University of Illinois, Urbana-Champaign, USA	11.5	14.0	Multi-spectral camera
ifgicopter	University of Münster, Münster, Germany	0.3	1.1	Temperature, Relative humidity
QuantaLab	QuantaLab IAS – CSIC, Córdoba, Spain	–	–	NIR camera
S GIS	University of Hohenheim, Stuttgart, Germany	2.0	4.3	Spectrometer, RGB camera
Smart Skies	Australian Research Centre for Aerospace Automation, Brisbane, Australia	–	12.3	Laser, stereo camera
VIPtero	National Research Council, Firenze, Italy	1.0	–	Multi-spectral camera

of having direct or very close contact to the analysed object (Tremblay et al., 2011).

3.2.2 UAS for environment and weeds

The µDrones project (Micro Drone Autonomous Navigation for Environment Sensing) project, completed in 2010, dealt with topics monitoring public and private sites, as well as the support of security teams in their work (µDrones, 2013). From the results concerning hardware and software config-urations, adaptions to related fields like agriculture can be done easily. In 2010, Acevo-Herrera et al. (2010) published their results of airborne soil moisture mapping in cereal and vineyard fields with a small UAS. Using a light radiometer at 1.4 GHz, they achieved low absolute errors in homoge-neous fields. Merz and Chapman (2011) used an autonomous helicopter for RS missions in unknown environments. The copter has been successfully deployed for autonomous im-age capturing for plant phenomics studies, and later, in a use case, Geipel et al. (2011) presented how to detect weed spots with a multicopter and offer it as a service for PF. As the occurrence of weeds has a major influence on crop yield, the classification of weeds and the detection of weed patches play an important role in agricultural research. Segmentation

and classification rules over arid rangelands (Laliberte and Rango, 2008) and over crops (Peña-Barragán et al., 2012) showed satisfactory and accurate results for species, group of species and for crop rows. Inside the RHEA project, Peña-Barragán et al. (2012) are using a multispectral camera on a multicopter for weed detection. The classification of image mosaics can be used for mapping and monitoring purposes. The demonstrated approaches are efficient and scalable for classification of similar vegetation.

Mapping of Mediterranean riparian forests was the focus of Dunford et al. (2009). They achieved overall classification accuracies of 63 % and 71 % for four species-level classes.

3.3 Autonomous platforms and swarm technology

In the near future, sensor platforms used in agriculture can become a smaller and smarter form of a robot. In reporting the experience of Nielsen et al. (2006), two criteria have to be taken into account regarding the development of an agri-cultural robot: (1) tool changing with dynamic adoption to new applications with necessary implements, and (2) human intervention so that the operator is able to change and influ-ence the system due to current and future needs. Based on the thesis of Appel and Nielsen (2005), Nielsen et al. (2006)

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Table 7. Commercial suppliers of rotary and fixed wing hardware. Product name is linked to more information. Latest information 7 May 2013.

Company	Product name	Country
Micro rotary wing/multicopter (≤ 5 kg)		
Aeroquad Carancho Engineering LLC	Aeroquad	San Pedro, CA, USA
AirRobot GmbH & Co. KG	AR 100-B/120/150/200	Arnsberg, Germany
Ascending Technologies GmbH	Falcon 8	Krailling, Germany
Draganfly Innovations Inc.	Draganflyer	Saskatoon, SK, Canada
EMT Ingenieurgesellschaft	FANCOPTER	Penzberg, Germany
Fly-n-Sense	Scancopter X4/X6	Mérignac Cedex, France
geo-konzept GmbH	X2000, X8000	Adelschlag, Germany
Gyrofly Innovations	Gyro 200/500	São José dos Campos, SP, Brazil
microdrones GmbH	microdrone	Siegen, Germany
Mikrokopter HiSystems GmbH	MikroKopter	Moormerland, Germany
Multirotor	MR-X8	Berlin, Germany
Novadem	U130, NX110m	Meyreuil, France
PC Quadrat GmbH	X3D-BL UFO	Nuremberg, Germany
service-drone.de GmbH	G3	Berlin, Germany
Survex Copter	Copter 1b/City/4	Pierrelatte, France
Micro fixed wing (≤ 5 kg)		
AGX Tecnologia Ltda	Tiriba	São Carlos, SP, Brazil
CALMAR Mapping Services	CALMAR Crop Condor	Remington, IN, USA
CropCam Inc.	CropCam	Stony Mountain, MB, Canada
Fly-n-Sense	Seeker 1300	Mérignac Cedex, France
Gatewing NV	X100	Gent, Belgium
Lehmann Aviation	LFPV, LM450, LP960, LV580	La Chapelle Vendômoise, France
SmartPlanes AB	Personal Aerial Mapping System	Skellefteå, Sweden
senseFly SA	swinglet CAM, eBee	Ecublens, Switzerland
Thamm Geo-Technic	Aurora, SUSI 62	Linz am Rhein, Germany
Mini Aerial Vehicle (< 30 kg)		
Aeroscout GmbH	Scout B1-100	Adliswil, Switzerland
AGX Tecnologia Ltda	AG Plane, Arara T1/M1	São Carlos, SP, Brazil
Delft Dynamics B.V.	RH2 Stern	JD Delft, Netherlands
SARL Infotron	IT180-5 TH/EL	Massy, France
Mini Aerial Vehicle/Close Range (< 150 kg)		
Swiss UAV AG	Neo, Koax, TU-150 Hybrid	Niederdorf, Switzerland

described further principals of multi-agent systems and the collaboration between robots. They outlined the Explorer-Transporter paradigm where the explorer consists of robot(s) for data acquisition in field and creating precise maps, and the transporter is the applicant of fertilizer or chemicals based on the information of the exploring unit(s).

Due to the smaller size and lower weight of future platforms, they will be less intrusive to soil. They will not be as weather dependent as today's big machinery, and will collect timely and accurate field information. The robots will be able to scout and treat each single plant individually (Blackmore et al., 2005). Blackmore and Griepentrog (2002) gave an outlook on autonomous platforms that may be available in the future. These autonomous platforms would be used for culti-

vation and seeding, weeding, scouting, application of fertilisers and chemicals, irrigation and harvesting and would have the ability to work in teams as multi-units (McBratney et al., 2005).

A further logical step from automation and autonomy of mobile platforms is "swarm technology" or "swarm intelligence". Karaboga and Akay (2009) surveyed algorithms based on bee swarm intelligence. By adapting these approaches, several questions and challenges in research could be solved. To classify a swarm as having intelligent behaviour, Millonas (1992) defined the following five principles:

1. Ability to do simple space and time computations (the proximity principle);

2. Ability to respond to quality factors in the environment such as the quality of foodstuffs or safety of location (the quality principle);

3. No single allocation of all resources along excessively narrow channels and it should distribute resources into many nodes (the principle of diverse response);

4. No change of its mode of behaviour upon every fluctuation of the environment (the principle of stability);

5. Ability to change behaviour mode when the investment in energy is worth the computational price (the principle of adaptability).

Robot swarms are in development with an increasing interest from a number of researchers working on the topic. Aside from the Technical University of Braunschweig, Germany, the Fraunhofer Institute, Karlsruhe, Germany, the ETH Zurich, Switzerland, as well the University of Pennsylvania, Philadelphia, PA, USA, and the Center for Collaborative Control of Unmanned Vehicles at the University of California, Berkeley, CA, USA are all working in the field of UAS swarm intelligence (Bürkle et al., 2011; Schattenberg et al., 2011; Schoellig et al., 2012; Kushleyev et al., 2012). In the future, multiple vehicle units will also be capable of path planning and interacting within a whole fleet (Barrientos et al., 2011; Cartade et al., 2012). To prevent collisions, or for exploration tasks, the absolute positioning of all the swarm participants at every point in time is very important (Schattenberg et al., 2011). Adapting the approaches for multiple robot motion coordination, autonomous vehicles moving along independent paths will be able to avoid mutual collisions (Siméon et al., 2002). The research team Bry et al. (2012), from the Massachusetts Institute of Technology (MIT) in Cambridge, USA, has already reached a further step in this challenge. They developed algorithms for autonomous control of an indoor GPS-denied UAS and successfully tested an indoor flight in an underground parking lot.

4 Discussion

With manually driven, partly automatic, completely autonomous mobile sensor platforms or robots, an increased sensor implementation is possible. Based on the knowledge of stationary industrial robots, operational outdoor sensor platforms and robots emerged in research. Due to constant, structured and predictable indoor working environments, the control and management of industrial robots can be done in an automated way. The implementation with the same safety and accuracy for field tasks is more challenging due to the rough and changing environmental conditions which

are changing dynamically and continuously. Variability or heterogeneity in agricultural fields are caused by many natural factors like terrain, soil, vegetation, illumination, visibility and other atmospheric conditions like wind or humidity, which vary in time and space, and are characterized by rapid changes (Bechar and Edan, 2003). These uncertainties make it challenging for sensor data acquisition outdoors and more variables have to be taken into account for sensor calibration and set-up. Factors which might have negative influences on sensor measurements whilst using them on sensing platforms are (1) vibrations due to the type of propulsion, (2) uneven terrain, (3) turbulences in air, (4) noise of the vehicle itself, (5) pollution, dust or particles in the surrounding area, (6) self-shadowing depending on the sun position and sensor height, (7) changes in illumination due to clouds, (8) the distance to the desired measurement object, or (9) the response time of the sensor itself (Agogino et al., 1995; Schilling and Jungius, 1996; Schulz et al., 2012). The energy consumed through the need for torque, for required maintenance of a complex carrying platform, and for staff to run the system, increase the acquisition process costs. Modifications of chassis require permissions and must fulfil certain legal requirements when a system is operated self-propelled on public roads for easier field changes or transportation, and even more for aerial or autonomous purposes. Nevertheless, higher ground coverage and more repeatable measurements per season with a continuous predefined set-up are the reasons why platforms are used at an increasing rate for sensing purposes and data collection in agriculture (Moran et al., 1997; Adamchuk et al., 2004; Keller et al., 2011). The results and approaches of these platform projects can accelerate the way from PF to smart farming (SF), where sensors used for a wide range of agricultural tasks are the goal. Smith (2002) noted in 2002 the term "smart" pertaining to farming. She focused on modern practices for reduction of variable production costs (Goodwin and Mishra, 2004). Stein et al. (2007) stated the necessity of appropriate procedures and support tools to increase time from data to management decisions, even more with a high amount of information as on modern farms. In farming systems, tractor-sensor combinations are still state-of-the-art for data collection and applying tasks. Online sensor approaches are preferred for reacting immediately to variable and heterogeneous field conditions, passing a field, and throughout the whole growing season. Combining larger scaled data from a UAS with the detailed point data from a ground-based vehicle offers a wider range of measurement values within a shorter time gap as well as other relevant information, e.g. from an aerial image. As a high and real-time data resolution is important for field treatments, small multicopter are promising tools to involve them in online data acquisition and application processes. Depending on the requirements of the data acquisition process, precise georeferencing is an important feature to locate measured data exactly, even more for RS, e.g. of a UAS (Bláha et al., 2012). Therefore a correction signal for the GPS device
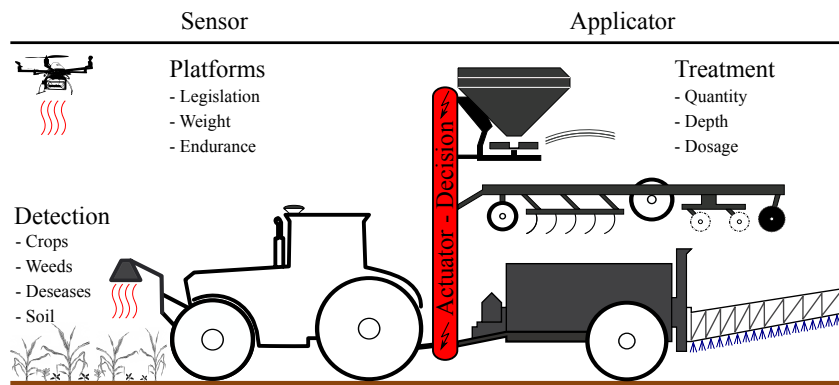
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Figure 2. Sensors on aerial and ground platforms for agricultural data acquisition. With the help of the measured data, the actuator controls the system and an agent/applicator carries out the treatment on the field.

on the UAS is necessary. To solve this issue, Rieke et al. (2011) worked in the topic of high spatial precision using RTK accuracy on a UAS system to detect heterogeneity in fields.

As the presence of weeds and grass weeds reduces crop yield significantly, weed management is an important field application. In PF many efforts have already been made and are in development with regards to reducing herbicide application amounts to protect the environment and reduce treatment costs. Ultrasonic systems can be used for weed detection, as well as red and infrared images are used for weed detection and species discrimination. Andújar et al. (2011) described detection success of 81 % in pure stands of grasses and 99 % in pure stands of broad-leaved weeds with an ultrasonic sensor. Recently, Andújar et al. (2012) predicted weed presence in more than 92 % of the cases. Herbicide use has been reduced up to 81 % by using bi-spectral cameras for online detection of weeds and a map-based approach for site-specific spraying (Gerhards and Oebel, 2006). To develop an online weed detection and application system, faster response time for decision and spraying components is required (Weis, 2010). Response time of sensor systems is a main criteria and aimed to be as short as possible (Schulz et al., 2012).

In order to provide a versatile and cost-effective crop monitoring system, Øvergaard et al. (2010) suggested using a lightweight, specifically designed spectral device for a UAS. Instead of expensive sensors, the focus of recent projects have also low-cost consumer devices like digital cameras. With little technical changes inside the device by removing the internal NIR blocking filter, cost-effective quantitative monitoring with good precision is possible. This principle was used in the mid-1990s by Everitt et al. (1995). However, many technical aspects still have to be improved, like the location of spectral bands or the potential for reflectance calibration (Lelong et al., 2008; Hunt Jr. et al., 2010).

As most commercially available sensors are based on the signals of a single sensor, this can lead to misinterpretation of the situation in the field (Zillmann et al., 2006). Samson et al. (2000) showed that nitrogen and sulphur deficiencies have different effects on the laser-induced fluorescence spectral signatures of a field sensor. If these deficiencies were taken into account, by using a sensor capable to detect this effect together with other sensors, management decision would be more reliable and accurate. Mixed sensor signals can be another limitation due to an inexactly defined measurement spot to the canopy. Especially in spectrometry, these signal overlays of plants and soil affect the measurement quality. A solution to this problem is the spectral imaging technology where spectral information for each single pixel is available (Ruckelshausen, 2012). Also for electrical conductivity measurements data of other sources, e.g. of soil moisture, are needed to correctly interpret the values (Dabas et al., 2000; Adamchuk et al., 2004). According to Adamchuk et al. (2010), more robust sensor solutions with higher reliability will become available for agricultural decision-making with the integration of greater quantities of sensor data. Regarding the actual discussed topic smart farming, fusion techniques of a large amount of data sources from mission sensors, as well as navigation sensors will play an important role. Therefore, on the one hand, easy to use decision support systems for the operator or farmer are necessary. On the other hand, standardised system components are required. The ISOBUS machine communication of the agricultural and forestry industry, standardises e.g. connection plugs and data formats. Through this standard, the data output of a sensor can be analysed in the system, taken into account by the actuator and be sent as a decision to the applicator (see Fig. 2). The work for ISOBUS and other standards is ongoing. It will be mandatory for future system solutions, having standardised interchange of internal (machine) and external (e.g. database, UAS) data, as well as of system components.

5   Conclusions

Within the last fifteen years more and more technology from research areas, like the defence sector or sensor engineering, were also implemented into agricultural research and practice. Systems for automatic steering, site-specific crop treatment or data mapping are quite common on modern farms. More powerful electronics, inside of smaller and lighter devices with robust performance, opened the door to new technological approaches in agricultural fields. With these kinds of electronic aids becoming available, there has been greater advancement within the areas of methods and applications. Consequently, the idea of using mobile sensor platforms in agricultural research has become more popular. However, by building up a mobile sensor platform for agricultural purposes, several steps need to be taken into account. The categorisation tree in Fig. 1 provides an overview of relevant modules and information on how mobile sensor platform can be categorised in general.

The main focus of this paper was to clarify, which mobile sensor platforms are already in use or in development, especially in recent agricultural and closely related science projects. It has become evident that there are several platforms available for sea, ground and air usage. Many platforms are currently in use and listed in Table 5 for ground vehicles and Table 6 for unmanned aircraft systems (UAS). A choice can be made between an offline approach (measurement, calculation, and application are separate steps) or an online approach (sensor and direct application) with active or passive sensors. The availability of sensors is huge and can be adapted to the necessary task based on optical, thermal, magnetic, acoustic, mechanical, or chemical measurement methods. Especially mobile sensor platforms, using different sensor systems simultaneously, provide the possibility of comparisons and tests of new sensor approaches, and thus, help to develop suitable sensor systems for precision farming (PF). By implementing multiple sensors on vehicles and in practical application cases, their integration as redundant, complementary or cooperative configuration offers more reliable and more robust decision-making.

Ground platforms and UAS were described that are working either in manual, automatic or autonomous ways. The more advanced the degree of automation is, the more fundamental obstacle detection and collision avoidance are for control processes that can be assured by several sensors. Fusion of the gathered information is an essential part of multi-data sources. Information fusion was presented and the architecture models implementing these algorithms are outlined in this manuscript. With this review it was obvious that mobile sensor platforms are able to be applied to mapping, monitoring, scouting and applying tasks in agriculture. The detection of weed or nutrient status in crops are two examples for scouting and monitoring tasks. Further advanced applications still remain at research level.

As the implementation of mobile sensor platforms in agriculture is still at the very beginning, there are several knowledge gaps which need to be solved in the near future. In PF, the goal of growing more and having better output with less input is reflected in practice by the use of sensor technology in applying a more efficient quantity of fertilizers and less chemicals in fields. Sensor-based measurements in agriculture are already used efficiently for site-specific treatments in crops. But the usability of decisions support systems for the farmer still needs to be improved for easier management (see Fig. 2). In agriculture, mainly online sensor solutions for nitrogen application or growing height are developed. However, the causes for variability in the field must be adequately understood before sensor-based decisions can safely be used. Usable online systems for weed detection, crop diseases or water status of the plant are still lacking.

Future applications in agriculture seem to have a strong need for mobile sensor platforms according to the increasing number of agricultural research topics involving ground and aerial vehicles. New sensor approaches with multiple sensors can be developed, compared and tested with these platforms by fusing information for knowledge discovery. More operable systems for the final user with direct decisions made by a task controller in the machine are desired on farms. Mobile sensor platforms are most commonly used in monitoring and scouting applications. Currently, many of these projects are dealing with the detection of soil and plant characteristics (see Table 5). Here, UAS are promising platforms for real-time data equipped e.g. with modified digital cameras.

Sensor technology enables the protection of the environment and the use of resources efficiently, whilst at the same time allowing for even crop development and better harvest qualities. In the future, advanced platforms or robots also need to have the ability to apply, e.g. nutrients or pesticides to a defined management field zone or even to the single plant specifically. Recent research projects dealing with automatic or autonomous robots and swarm technology have been described in this review. Future projects will involve swarm intelligence and swarm behaviour on vehicles or platforms in many application areas.

Depending on the intensity of cultivation and the growing region, there will always be different technology levels of platforms. The market, product quality, environmental concerns of each country, labour costs and human safety will either require middle or high technology level.

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3 Fluorescence and Reflectance Sensor Comparison in Winter Wheat

For the investigations of this publication two spectrometers and one fluorescence sensor were used in wheat (*Triticum aestivum* L., cv. Toras) field trails. The sensors were mounted on a multi-sensor ground platform ("Sensicle"), used for investigations at the research station Ihinger Hof, Renningen (Germany), in continuous measurement mode. The research about three years was done on field trials with different N levels ranging from 60 to 180 kg N ha^{-1} in six distinct levels.

The results showed positive correlations with wheat yield and available N for the Normalised Difference Vegetation Index (NDVI), the Optimised Soil-Adjusted Vegetation Index (OSAVI), the CropSpec index and the Red-Edge Inflection Point (REIP) of the used spectrometers. With the growing stages reaching plant senescence, the indices show a decreasing correlation due to chlorophyll degradation.

The fluorometer Multiplex® Research has not been used in wheat field trails before. The Fluorescence Excitation Ratio Anthocyanin Relative Index (FERARI), Far-Red Fluorescence index (FRF) and Simple Fluorescence Ratio (SFR) showed positive correlations with yield, N uptake and available N to the plant, with increasing Adj. r^2 values the later the growing stages became.

The authors present four predication models for single or mixed sensor parameters, with fluorescence signals and ratios as well as spectral indices. A linear model, containing a mix of one fluorescence signal and two spectrometer indices, showed high correlation for the prediction of wheat yield over the whole growing period. The authors conclude with a recommendation for sensor feature combinations containing proximal fluorescence sensor and spectrometer attributes.

Fluorescence and Reflectance Sensor Comparison in Winter Wheat

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Abstract: Nitrogen (N) is the most important macronutrient in plant production. For N application, legislation requirements have raised, and the purchasing costs have increased. Modern sensors can help farmers to save costs, to apply the right quantity, and to reduce their impact on the environment. Two spectrometers and one fluorescence sensor have been used on a vehicle sensor platform for N detection in wheat (*Triticum aestivum* L.) field trials over three years. The research fields were divided into plots, and the N input ranged from 60 to 180 kg N ha^{-1} in six levels. The OSAVI (optimized soil-adjusted vegetation index) showed a similar value pattern to the NDVI (normalized difference vegetation index) and the CropSpec index for the investigated factors. The red-edge inflection point (REIP) index showed high correlations to N (indicated by r^2 between 0.6 and 0.8), especially in June and July. The developed models from the fluorescence indices FERARI, NBI$_R$, FLAV, and the spectrometer indices CropSpec and HVI show high correlations ($r^2 = 0.5$–0.8) to yield and may be used for future yield predictions. The Multiplex Research™ fluorescence sensor (Force-A, Orsay, France) was the most convenient sensor with a simple measurement method and a non-proprietary file output. The implementation into existing agricultural vehicle networks is still necessary, being able to use it on a farm for online N recommendations.

Keywords: agriculture; precision farming; sensors; indices; comparison; nitrogen; yield; wheat (*Triticum aestivum* L.)

1. Introduction

Nitrogen (N) application in agricultural crops improves the crop yield (quantity) and increases the protein content (quality). Therefore, it is used in huge quantities as fertilizer all around the world [1]. If the chemical compound N is not available to the plants (e.g., through denitrification, or if the crop cannot metabolize all the available N in the form of nitrate, NO_3, or ammonium, NH_4^+), N leaching can cause vast environmental pollution [2].

Governmental restrictions and documentation duties, along with a stronger public awareness of environmental safety, led farmers to plan their fertilizer applications more carefully. Increasing prices for fertilizers over the last years pressured today's farmers even more to reduce farm inputs and save costs in agricultural applications.

Sensors using the principles of reflectance or fluorescence measurements are very useful tools to provide support in this area. Sensors enable site-specific fertilizer treatments in dedicated management zones or variable N rates over a whole field. A steady crop development over the whole field and a homogeneous grain quality (protein content) are the main aims of their usage.

Sensor analysis—especially reflectance measurements with spectrometers—have been used in precision farming (PF) applications for decades [3], as more than 90% of the spectral information about the crop canopy status are contained in the red and near-infrared (NIR)

spectral bands (e.g., [4,5]). A nitrogen limitation in plants results in higher reflections in the red spectral region, as a consequence of lower chlorophyll content in the plant cells [6]. Non-destructive methods have been developed to quickly determine the nutrition status in a field [7,8]. Narrow spectral bands from 1 to 10 nanometers (nm) enable the gathering of detailed information of the wavelength bands—an advantage of modern spectral sensors with high wavelength accuracy. Thomas and Gausman [9] showed that in the spectral band region from 400 to 700 nm, it is mainly chlorophyll and carotenoids that are absorbing the incident radiation. Spectral vegetation indices, calculated based on combinations of NIR and red spectral reflectance, showed good correlations with canopy parameters related to chlorophyll and biomass occurrence. The band regions of strong chlorophyll absorption (670 nm) and leaf reflection (780 nm) indicate a positive correlation to leaf area index (LAI) and chlorophyll content (e.g., [10,11]). Rasmussen et al. [12] concluded that chlorophyll is the most important independent factor affecting leaf reflectance.

A further interesting technology is the sensing of fluorescence. It allows for non-destructive measurements of chlorophyll content, N/C ratio, or leaf area index [13]. Fluorescence techniques in agricultural vehicles are still barely in use. Reasons for that are a lower surface capture and the need of a close distance to the crop canopy, accompanied by leaf excitation always with the same amount of light energy and the absence of background noise (e.g., of the soil) [14]. Other available field-based fluorescence measurements (e.g., high-resolution spectroradiometers [15] or hyperspectral line scanners [10]) do not have the requirements of being very close to the canopy or exposing the plants to active excitation (sun-induced fluorescence). Their suitability for fluorescence measurements is still in discussion, and is not a subject in this publication, which will focus on using active techniques to measure chlorophyll fluorescence.

This publication compares the data of two spectrometers and one fluorescence sensor from investigations in agricultural fields. It aims to answer the questions:

- Which sensors have been the most useful in regards to practical field handling?
- Which indices are statistically significant for assessments of the N treatments?
- Which fluorescence and spectroscopy indices can be used to estimate the wheat yield at an early development stage; i.e., what kind of index combination can derive a more exact yield prediction?

2. Materials and Methods

2.1. Experimental Site

The field trials were conducted at the research station Ihinger Hof, Renningen (Germany), an institution of the University of Hohenheim, Stuttgart (Germany). The site Ihinger Hof (N 48°44′41″, E 8°55′26″) has a mean annual precipitation of 690 mm and a mean temperature of 7.9 °C. From 2010 to 2012, the measurements were carried out in winter wheat (*Triticum aestivum* L., cv. Toras) on the experimental fields "Inneres Taele" (IT) and "Lammwirt" (LW). Due to crop rotation aspects, the N sensing field trial was continued on field IT in the second growing season. These two fields have a high natural field variability, with soil types reaching from pure clay to silty loam. The EM38 is an instrument for near-surface soil conductivity survey measurements, and measured values of 52–86 millisiemens (mS). Figure 1 shows the experimental field design. The experimental fields were divided into several plots of 36 × 36 m, each plot separately into 36 × 12 m strips. The randomized N amounts ranged from 60 to 180 kg N ha^{-1} in five levels (N1 to N5), beside an N dosage of 170 kg N ha^{-1} (K). Variant K represents the N dosage that is usually applied on this farm. The total N amount was split into three applications over the early growing period. The first and second times, the fertilizer was applied in the tillering stage, and the third time took place between stem elongation and booting stages (Zadoks-scale) [16,17]. The first N dosage was applied equally over the whole field. The second and third passages were carried out as variable N applications to achieve the planned final N amounts for each plot. Each N treatment was applied with a pneumatic fertilizer spreader and a tractor with an automatic steering system and GPS-RTK precision (approx. ±2.5 cm).
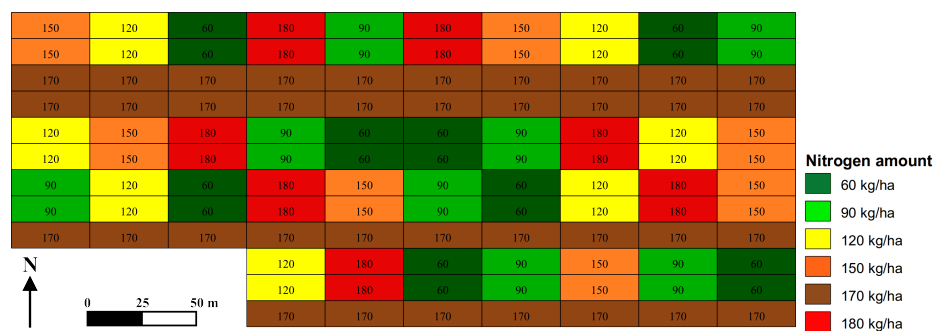
Figure 1. Layout of the experimental field design, here shown for the "Lammwirt" field. The numbers within the plots show the applied nitrogen dosage per year, expressed in kg ha^{-1}. The total N amount has been split into three passages over the field. The varieties with 60 to 180 kg N ha^{-1} (N1 to N5) have been randomly distributed besides the conventional variety with 170 kg N ha^{-1} (K).

Soil samples of all strips were taken in spring, before crop growth continued, and again after harvesting the research fields. The soil samples were analyzed to determine the available nitrogen in the soil (N$_{min}$-method) for three soil depths: (1) 0–30 cm; (2) 30–60 cm; and (3) 60–90 cm. Biomass samples over the whole field were collected at three growing stages: (1) stem elongation; (2) flowering; and (3) right before harvest. In a laboratory, these biomass samples were dried and analyzed regarding the number of grains per ear, the number of tillers, the protein content, and the biomass weight. The yield data were gathered by a standard New Holland combine with a header of 6 m cutting width.

2.2. Sensor Set-Up

The measurements have been derived with three sensors: (i) FieldSpec Handheld (Analytical Spectral Devices, Boulder, CO, USA); (ii) HandySpec Field (tec5 AG, Oberursel, Germany); and (iii) Multiplex Research™ (Force-A, Orsay, France) (Table 1).

Table 1. Used sensor devices and sensor details.

Type	Manufacturer	Sensor Model	Wavelength Range	Wavelength Accuracy	Classification
Spectrometry	Analytical Spectral Devices	FieldSpec Handheld	325–1075 nm	1 nm	Passive
	tec5 AG	HandySpec Field®	360–1000 nm	10 nm	Passive
Fluorescence	Force-A	Multiplex Research™	Blue-Green (BGF), Red (RF) and Far-Red (FRF)	–	Active

They were mounted on the self-propelled sensor platform "Sensicle", a rebuilt Hege 76 multi-equipment carrier (Wintersteiger AG, Ried, Austria) (Figure 2) driven by the author. The three sensors were used in a three-year field experiment with randomized N replications (Figure 1).

Figure 2. The multi-sensor platform "Sensicle" with the mounted sensors.

2.3. Spectrometry

The FieldSpec Handheld used in this research set up has a spectral range from 325 to 1075 nm with a 1 nm wavelength accuracy and a field of view of 25°. It was mounted at a height of 200 cm above canopy, resulting in a measuring surface of 2.74 m². The reflectance was calculated based on an additional measurement of a given white standard (BaSO$_4$). The HandySpec Field has a spectral range from 360 to 1000 nm with a 10 nm accuracy and a field of view of 25°. It was mounted at a height of 80 cm above canopy with a measuring surface of 0.44 m². The integration time was set to automatic mode, and varied between 25 ms and 128 ms. Before starting each measurement series, a spectralon plate was used for white calibration purposes with both devices. A white standard is used to optimize the two spectrometers to the current illumination.

Both spectrometers are passive sensors. From the raw data of these spectrometers, several vegetation indices were calculated to be used for the crop status analysis. In the following, *R* denotes the reflectance, the sub-index the wavelength in nm. The simple ratio CropSpec can be used to measure the site-specific N nutrition status of crops [18–20]. The normalized difference vegetation index (NDVI) is an indicator of greenness and a transformation of the infrared-red indices. The higher the value of the NDVI, the greener the foliage [21–23]. Furthermore, the NDVI correlates mainly with absorbed photosynthetic active radiation [24]. The hyperspectral vegetation index (HVI) has been used based on a previous study with the same FieldSpec HandHeld sensor [25]. It is a modified index for analyzing satellite spectral data [26]. The optimized soil-adjusted vegetation index (OSAVI) is a derivative of the soil-adjusted vegetation index (SAVI), and minimizes soil brightness influences from spectral vegetation indices involving red and near-infrared wavelengths [27,28]. The factor *L* varies between 0 and 1. As foliage density increases, the selected value of *L* must decrease. [29,30]. The red-edge inflection point (REIP) is a strong indicator of the chlorophyll content [31–33]. The higher the value of the REIP, the better the chlorophyll status [34].

$$CropSpec = \left(\frac{R_{808}}{R_{735}} - 1\right) \times 100 \tag{1}$$

$$NDVI = \frac{(R_{780} - R_{680})}{(R_{780} + R_{680})} \tag{2}$$

$$HVI = \frac{R_{750}}{R_{700}} \tag{3}$$

$$OSAVI/SAVI = \frac{(R_{800} - R_{670})}{(R_{800} + R_{670} + L)} \times (1 + L) \tag{4}$$

$$REIP = 700 + 40 \times \frac{(R_{670} + R_{780})/2 - R_{700}}{R_{740} - R_{700}} \tag{5}$$

2.4. Fluorescence

Fernandez-Jaramillo et al. [35] have reviewed chlorophyll fluorescence sensing methods, concluding in the broad application area; e.g., for the detection of environmental impacts, as well as the need for an embedded sensor system to reduce measurement efforts. The used fluorescence sensor Multiplex Research™ is a mobile embedded sensor. It was fixed on the "Sensicle" such that the opening was always touching the canopy surface. So, while driving, the plants passed directly within the 8 cm diameter (50 cm^2) opening of the sensor, in a defined distance to its detection zone. The fluorometer was set to continuous measurement mode. It records twelve fluorescence signals and calculates chosen ratios [36]. Each fluorescence signal value contained the mean of 125 single measurements. Several light-emitting diodes (LEDs) at 375 nm UV-A (UV), 530 nm green (G), and 630 nm red (R) are used as light source to excite the crops. The Multiplex sensor is insensitive to ambient light, as the LED sources are pulsed and synchronized to the detection [37]. In comparison to the calculated vegetation indices of spectrometers, the three synchronized detectors of this fluorescence sensor record the ratios based on fluorescence emission at blue-green (BGF), red (RF) and far-red (FRF). The following indices of the sensor have been used: chlorophyll fluorescence excitation ratio (FER), linked to shielding of leaves by polyphenolics and flavonols; nitrogen balance index (NBI), linked to epidermal phenolics and chlorophyll contents; simple fluorescence or chlorophyll ratio (SFR), linked to the chlorophyll content; and FERARI and flavonol index (FLAV) as logarithms of FRF and FER. The subindex denotes the wavelength excitation of the LEDs.

$$FER_{RUV} = \frac{FRF_R}{FRF_{UV}} \tag{6}$$

$$FERARI = \log\left(\frac{5000}{FRF_R}\right) \tag{7}$$

$$FLAV = \log(FER_{RUV}) \tag{8}$$

$$NBI_R = \frac{FRF_{UV}}{RF_R} \tag{9}$$

$$SFR_R = \frac{FRF_R}{RF_R} \tag{10}$$

More detailed information about the Multiplex Research™ sensor, the fluorescence technology, and the fluorescence indices is available in Cerovic et al. [38] and Ben Ghozlen et al. [7].

2.5. Data Analysis

For calculation of the indices from the raw sensor values, the R packages hyperSpec [39] and ggplot2 [40] have been used. Statistical analysis procedures of linear and polynomial regressions, as well as an analysis of variance (ANOVA) were applied to the indices of the spectrometers and the fluorometer to distinguish between the N treatments, measurement dates, yield, available N, and the N uptake of the biomass. The focus is on sensor comparison.

3. Results

The following will present the results of the field investigations carried out in the years 2010, 2011, and 2012 at the research station Ihinger Hof, Renningen (Germany).

Three sensors were used in the three seasons of field research. Each sensor had to be connected or handled in a different manner, in order to be able to gather valuable data (see Table 2).

Table 2. Ease of use of the three used sensors and their handling capabilities.

Sensor	Operating System	Connectivity	Ease of Use
FieldSpec HandHeld	Windows NT	Serial cable to PC	Complex (–)
HandySpec Field®	All	SD Card	Easy (0)
Multiplex Research™	All	SD Card	Simple (+)

3.1. Field Conditions

The average growth of the wheat plants over the three years of field trials can be seen below (Figure 3), represented in the international growing stages scale (Zadoks-scale) [16,17]. From a plant development perspective, each year the stem elongation started half a month earlier than the previous year. The growing conditions over the three years of field trials were very similar, with sufficient rainfall and no period of drought.
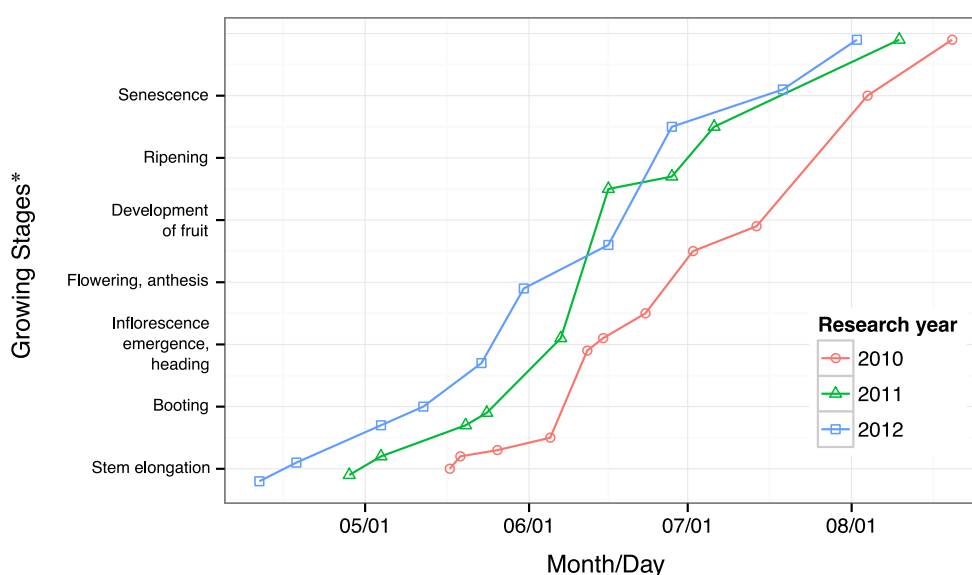

Figure 3. Wheat growing stages (Zadoks-scale) for the three years of field experiments. Only the main growing stages appear in the graphic. Each symbol on the graph represents the date of measurement. The last measurements were taken right before the harvest. * Germination, leaf development, and tillering stages are not shown.

Table 3 shows the mean yield data as well as the protein content of the three experimental years. In 2010, the experimental field Inneres Taele (IT) showed a higher field variability in terms of crop density and soil type than the experimental field Lammwirt (LW) in 2010 and 2012. Furthermore, the increase in the average yield and protein content in the IT field in 2011 did not vary as much between the different N treatments as for the LW field in 2010 and 2012. This can be seen in the mean yield data of field IT in 2011, especially for the treatment area with 60 kg N ha^{-1}.

For all replications, the yield had its maximum at 170 kg N ha^{-1}. The protein content for the years 2010 and 2011 increased over all N replications from 60 to 180 kg N ha^{-1}. Less protein was metabolized in the year 2012 in the LW field in the plots with 180 kg N ha^{-1} .

The following two subsections refer specifically to the example of the data of investigation year three (2012) from the LW research field.

Table 3. Average grain yield (t ha^{-1}) and grain protein content (% in dry matter) of winter wheat (*Triticum aestivum* L.) for six different N levels during three years of field experiment. "IT" marks the experimental field "Inneres Taele", "LW" the experimental field "Lammwirt". Both fields are located at Ihinger Hof, Renningen, Germany.

| Parameter | Field | Year | Annual Nitrogen Application in kg ha^{-1} | | | | | |
			60	90	120	150	170	180
	LW	2010	3.6	3.9	4.4	4.5	4.9	4.5
Yield	IT	2011	7.2	6.7	6.7	7.1	7.3	7.3
	LW	2012	6.2	6.5	7.5	7.8	7.9	7.9
	LW	2010	11.2	11.9	12.3	14.1	14.8	15.5
Protein	IT	2011	13.5	13.5	14.3	13.9	14.7	14.7
	LW	2012	9.1	10.1	11.4	12.7	13.6	13.2

3.2. Regression Analysis

A data analysis with a high temporal and spectral resolution results in better insight and higher significance levels. Figure 4 represents the NDVI value in correlation to the wheat yield, split by measurement dates and nitrogen amounts.
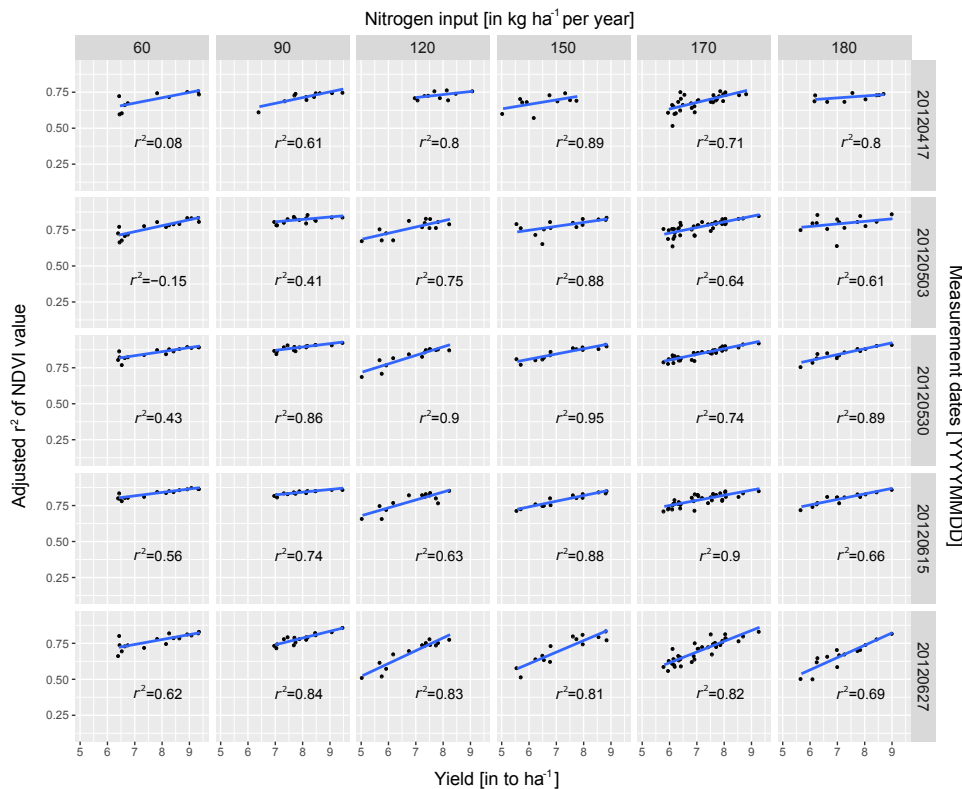

Figure 4. Adjusted r^2 values for normalized difference vegetation index (NDVI) of measurement period 2012 in wheat (*Triticum aestivum* L.) field "Lammwirt", gathered with FieldSpec HandHeld spectrometer, class-divided by measurement dates and nitrogen input. Adj. r^2 shows the percentage of variation explained by the independent variable (NDVI) that affect the dependent variable (yield).

Relevant indices of the two used spectrometers are shown in Figures 5 and 6, with averaged measurements over all N levels of the research field LW. The measurement dates in 2012 for the HandySpec Field (*.x) were not as frequent as for the second spectrometer, the FieldSpec HandHeld (*.y). Indices of both spectrometers did not correlate on a high level with the "N uptake". The NDVI

of the FieldSpec sensor showed an r^2 value saturation for "Yield" and "Available N", starting in mid-June 2012.
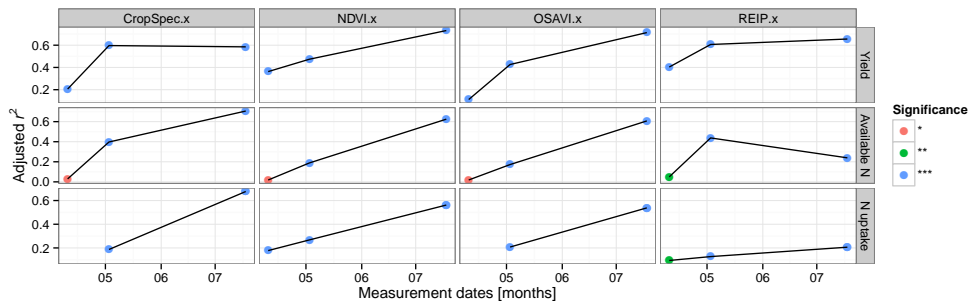

Figure 5. Adjusted r^2 values for indices of HandySpec Field (*.x) sensor over the 2012 measurement period. The colour expresses the different significance levels: *** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05.
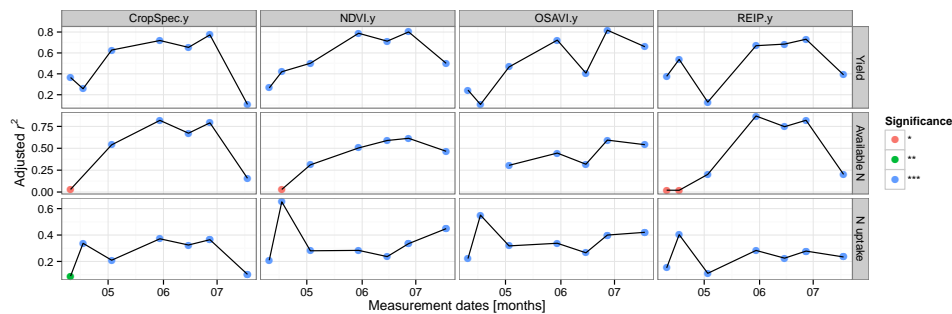

Figure 6. Adjusted r^2 values for indices of FieldSpec HandHeld (*.y) sensor over the 2012 measurement period. The colour expresses the different significance levels: *** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05.

Figure 7 visualizes the important fluorescence indices in the red area of the Multiplex Research™ sensor during the 2012 growing season for all N levels. The further the wheat plants were developed, the more precise these indices were, and the better they could predict "Yield" or "N Uptake"; meanwhile, the prediction for "Available N" remained low.
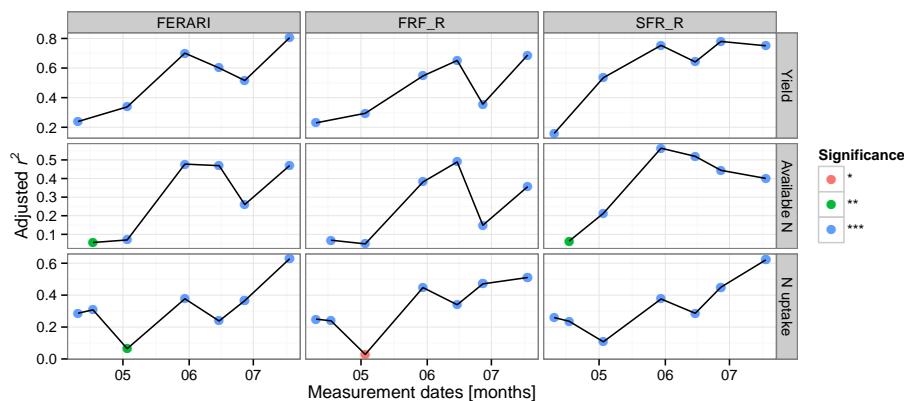

Figure 7. Adjusted r^2 values for indices of Multiplex Research™ fluorescence sensor over the 2012 measurement period. The colour expresses the different significance levels: *** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05.

3.3. Data Validation

The ground truth data have been added to each data set of the different measurement dates. Each data set has been intensively statistically analyzed to find the highest correlations for each field parameter. Table 4 shows the r^2 values of three different linear regression models with one, two, and three fluorescence parameters. The fourth model takes two spectrometer indices of the FieldSpec HandHeld sensor and one fluorescence signal into account. All models are grouped by the different measurement dates in the year 2012. The parameters A_x, B_x, C_x, and D_x denominate the modeled coefficients of the linear regressions:

Model 1: $y_1 = A_1 + B_1 \times FERARI$
Model 2: $y_2 = A_2 + B_2 \times NBI_R + C_2 \times FERARI$
Model 3: $y_3 = A_3 + B_3 \times NBI_R + C_3 \times FERARI + D_3 \times FLAV$
Model 4: $y = A_4 + B_4 \times CropSpec.y + C_4 \times HVI.y + D_4 \times RF_{UV}$

Table 4. r^2 values of four linear regression models with fluorescence and spectrometer indices, grouped by the different measurement dates in the year 2012 on field LW. All linear models are significant with *p*-values < 0.05.

Date	17 April 2012	3 April 2012	30 May 2012	15 June 2012	27 June 2012	18 July 2012
Model 1	0.11	0.38	0.62	0.57	0.51	0.74
Model 2	0.12	0.48	0.63	0.58	0.52	0.76
Model 3	0.22	0.52	0.64	0.59	0.54	0.76
Model 4	0.53	0.53	0.80	0.76	0.78	0.21

The models show the ability of the sensor indices to predict grain yield towards the harvested grain yield over all N levels of the research field LW.

4. Discussion

The field plots with a total applied nitrogen amount of 60 and 90 kg N ha^{-1} had a similar grain yield and grain protein content (Table 3). Regarding yield, it was obvious that the additional 10 kg of N from 170 to 180 kg N ha^{-1} had no effect on the grain quantity or quality. Besides the artificially-designed heterogeneity, the climatic conditions during the growing periods may have added to this effect [41].

Comparing the yield of field LW in 2010 and 2012 showed a 40% yield increase over all N varieties in 2012, hence it had a similar high yield level as field IT in 2011. The reason for the high yield in the IT research field can be explained by the previous crop in 2010, which was grain maize. Maize demands a high nitrogen supply, which may result in higher N residues in the soil at the end of the growing season. Consequently, the cultivated crop in the following year also has a higher N availability. Zhang et al. [41] investigated the important role of the crop rotation in the soil nutrient residues available to the following crop season. On both fields, maize was planted the year before. The effect of the available amount of nitrogen in the soil (N$_{min}$) from previous crops was not investigated further, as for example done by Sidhu and Beri [42] over the course of five years.

The sensor platform "Sensicle" (Figure 2) offers very good possibilities to take measurements with various sensors at the same time. After one season, a huge set of data was available. The correlations between all fluorescence and spectrometer indices and the ground truth data have been analyzed.

The most significant NDVI values—gathered with the mounted spectrometer FieldSpec—occurred in the stem elongation stage at the end of May (Figure 4). The lowest significance levels were in the stage of ripening, where chlorophyll is very low in the wheat plants. This identifies the NDVI once more as an index which is highly sensitive to chlorophyll (e.g., [43,44]). This high resolution in the analysis in terms of the splitting of the measurement dates and the N levels shows the highest correlations for NDVI and yield with r^2 values of 0.63–0.95 in the N level plots between 120 and 170 kg N ha^{-1}. For the plots with the lowest amount of N (60 kg N ha^{-1}), except for the two measurements in June, the correlations are low with a maximum r^2 of 0.43. In the early growing

stages until mid-May, these plots showed bare patches, uneven crop development, and consequently resulted in high background noise of the soil with significantly varying reflectance data. These effects in the early growing stages are also valid for the statistical analysis of Figures 5 and 6. After a closed canopy surface, the spectrometer indices (CropSpec, NDVI, OSAVI, and REIP) showed increasing values in correlation to "Yield", "Available N", and the "N uptake". For 2012, the HandySpec sensor detected a continuous increasing correlation with the ground truth data "Yield" and "Available N". Haboudane et al. [30] found that the OSAVI index is very sensitive to chlorophyll and is very resistant to LAI and illumination. In the field trials, OSAVI showed a similar pattern to NDVI and CropSpec index (Figures 5 and 6). The CropSpec index—developed by Reusch et al. [18] and integrated into a commercially available sensor for agricultural usage—correlated highly at the early growing stage with "Yield" and "Available N", and continued its performance until plant ripening started. The REIP index showed high correlations—especially in June and July, where the chlorophyll content was high. In the early crop season, the REIP index was in a similar r^2 value range, from 0.4 to 0.5, as the NDVI. All presented indices show their saturation at full crop development at the end of June, and the REIP index for "Available N" and "N uptake" even at an earlier stage. For the "N uptake" of the plant, analyzed in the laboratory, the spectrometer indices correlated only on a low level with r^2 between 0.1 and 0.55, having a maximum with NDVI at 0.63 in mid-May.

The strength of fluorescence measurements is their ability to sense information that cannot be sensed in other ways (e.g., how environmental stresses have damaged the photosynthetic apparatus) [45]. The analysis of the Multiplex fluorescence sensor data reveal better correlations to the ground truth data, as can be seen in Figure 7. Fluorescence techniques have been applied for nutrition detection purposes in agriculture for some years. Buschmann et al. [46] analyzed fluorescence emissions of plants by imaging blue, green, and red fluorescence. Tremblay et al. [14] provided a detailed review of the fluorescence measurement techniques, also discussing the results of the Multiplex Research™ fluorescence sensor. They concluded with a recommendation for this technique, as it allows for highly sensitive N information measurements, independent of background signal disturbances. Peteinatos et al. [28] investigated (amongst others) the significant signal differences between nitrogen-stressed and non-stressed plants. The FERARI index and the SFR index have a high level of correlation with the measured yield. The later the growing season, the better are the FERARI correlations for all three crop parameters. For the N uptake of the plant, all three indices—FERRARI, FRF and SFR—have a similar progression of the correlation. For the available N and the yield, all three values reach a saturation in June.

In the early developmental stages, all three sensors show low correlations with yield. The open crop canopy, with the bare soil in the background, may interfere too much. At the last measurement date, the grain was already in the senescence stage, with a lower content of chlorophyll. The indices of the FieldSpec Handheld sensor had higher correlations with "Yield" and "Available N" in the later development stages (Adj. r^2 of 0.5–0.8) than the indices of the HandySpec Field sensor (Adj. r^2 of 0.4–0.65). Reasons for this may be the minor quantity of measurement data, but also the lower sensor footprint area. For Model 4 (Section 3.3), only the CropSpec and HVI indices of the FieldSpec Handheld sensor could be used to get significant correlations with "Yield". The Multiplex sensor indices correlate on a high level with "Yield" (Adj. r^2 of 0.6–0.8).

Due to these high correlations, the authors developed equations with the NBI_R, FERARI, and FLAV indices of the Multiplex sensor and the CropSpec and HVI indices of the FieldSpec Handheld sensor, in order to enable a good yield prediction (Table 4). The combination of three fluorescence indices in a linear model showed the highest performance in the investigated field data set. The high correlation clearly shows the advantage of a good prediction capability for a sensor with active light emission and a close contact with the crop canopy. Combining two spectrometer indices together with a fluorescence signal also resulted in high correlations with r^2 values of 0.5–0.8 for the main growing season. Based on the equations, two sensors—or even more units in a row could be connected to work together as a fertilizer spreading system in the field for the early and main growing season of wheat.

5. Conclusions

The results of this paper have been obtained from trials conducted in the agricultural fields of a university research station, which has been integrated into the production cycle. Therefore, the data analysis may show a higher variability than data gathered in pot experiments or defined greenhouse conditions. The aim was to gain experience for the used sensors in real-time conditions, as well as to check and verify their usability for agricultural farm vehicles later on.

Out of the three used sensors on the Sensicle vehicle platform, the FieldSpec HandHeld spectrometer was the most complex (Table 2). In the version used, the required software was only compatible with a PC with Windows NT operating system. The sensor had to be connected to a computer via a serial cable, which was not necessary for the other two sensors used. Due to the necessary white reference measurements in changing illumination conditions, continuous measurements required stops for calibration. The FieldSpec HandHeld and the HandySpec Field spectrometers in their current hardware configuration are not usable on conventional farm equipment. Furthermore, their field of view is too low, considering the working widths of modern fertilizer spreaders between 12 and 40 m. Regarding usability and mobility, the Multiplex Research™ fluorescence sensor is more convenient for larger field measurement areas. The fluorescence sensor required only one calibration measurement at the beginning and only had to be mounted at canopy height. Then, the measurement could be set up continuously. This will allow—with several sensors over the whole working width—a useful integration into an application system containing a tractor and an implement. Both spectrometers require a high knowledge about their usage, the data processing, and decision making. For an average farm, this may be too much time, and would require a dedicated data specialist for integration into the field applications as well as the import of the work order by the machines.

The spectrometers and fluorescence sensor gathered better data over a closed crop canopy. Regarding the fertilizer application, the early development stages are the important ones to support a good crop development and a high yield potential. An active light source enables continuous and longer measurements, especially as the illumination in field conditions often changes. The NDVI was highly correlated with the wheat yield for the N variants between 120 and 170 kg ha^{-1} until end of May, where the chlorophyll content was very high. This effect is and has been used in the first sensor systems for fertilizer applications. The OSAVI and CropSpec indices have a similar result pattern to NDVI. They are used in modern agricultural sensors (e.g., with active light sources). For the fluorescence sensing, the FERARI index and the SFR index had a high correlation level with the measured yield. These two indices, as well as FRF, reached a saturation in June. In the linear model, the combination of three fluorescence indices as well as the combination of two spectrometer signals and one fluorescence signal are a promising method for wheat yield prediction. The objectives of this study were met. The sensors, ground truth data, and prediction models will be further investigated.

The necessary fast processing units for converting the algorithms into decisions—being the basis for a spreader or a sprayer—are additional efforts that must be developed in order to have these or other new sensors available for use on farms. Currently, a great deal of expertise is still necessary to use the sensors correctly. (1) Calibration measurement(s) may be required (e.g., at changing illumination); (2) Export of the data from the sensor and importing them into software; (3) Connecting the sensor to a RTK-GPS system or ground referencing the data set afterwards; (4) Analyzing the data; and (5) Deriving decisions (e.g., for the next growing season and the fertilizer applications). Further field tests and the implementation into existing board computers of agricultural vehicles (e.g., via the ISO 11783 (ISOBUS) standard) are required to make these sensors a success in farming.

Author Contributions: Christoph W. Zecha gathered the field data, made the statistical analysis and wrote the manuscript. Johanna Link proposed the field trial design, supported the statistical analysis, and wrote the introduction. Wilhelm Claupein proposed the idea for this study and supported with editorial contributions.

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4 Utilisation of Ground and Airborne Optical Sensors for Nitrogen Level Identification and Yield Prediction in Wheat

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This paper combines the measurements of publication 2 including a third field and a fixed-wing unmanned aerial vehicle (UAV) as sensor platform. It describes four site-year studies with one fluorescence sensor and two spectrometers mounted on a ground sensor platform, and one spectrometer on a UAV. The authors analysed the sensor data based on correlations with the dependent variables (DV) yield, BM weight, leaf area index (LAI) and available N for the plant (N_{avail}). The investigations were done at the research station Ihinger Hof, Renningen (Germany) in winter wheat (*Triticum aestivum* L., cv. Toras and Schamane) fields with several distinct N levels. The sensor measurements were taken various times over the growing seasons.

The aerial spectrometer showed low correlations with the ground truth data for site-year 2 for BM weight and LAI with the indices HVI, NDVI, OSAVI and with REIP. For site-year 3, there were no correlations with the DV's. For the site-years 1 and 4, the quantity of the aerial data was too low.

The sensors on the ground, the Multiplex® Research fluorometer and the FieldSpec Hand-Held, showed very high correlations with N_{avail} and BM weight, and positive correlations with wheat yield. Regarding the fluorescence sensor, FERARI, SFR and the RF signal were significant, where for the FieldSpec Handheld spectrometer it were the indices CropSpec, HVI, OSAVI and NDVI as well as REIP. The indices of the HandySpec Field® spectrometer showed lower correlations over all site-year measurements.

The developed model for site-year 4 of publication 2 has been used for a cross-validation with the data sets of the other site-years. This model did not correlate with these data sets. However, by exchanging only one spectral index with a fluorescence ratio, it resulted in significant correlation for all site-years. These results show the advantage of prediction models with mixed sensor features (ratios, signals and/or indices), to overcome sensor limitations and to reach the best possible yields at each field.

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Utilisation of Ground and Airborne Optical Sensors for Nitrogen Level Identification and Yield Prediction in Wheat

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Abstract: A healthy crop growth ensures a good biomass development for optimal yield amounts and qualities. This can only be achieved with sufficient knowledge about field conditions. In this study we investigated the performance of optical sensors in large field trails, to predict yield and biomass characteristics. This publication investigated how information fusion can support farming decisions. We present the results of four site-year studies with one fluorescence sensor and two spectrometers mounted on a ground sensor platform, and one spectrometer built into a fixed-wing unmanned aerial vehicle (UAV). The measurements have been carried out in three winter wheat fields (*Triticum aestivum* L.) with different Nitrogen (N) levels. The sensor raw data have been processed and converted to features (indices and ratios) that correlate with field information and biological parameters. The aerial spectrometer indices showed correlations with the ground truth data only for site-year 2. FERARI (Fluorescence Excitation Ratio Anthocyanin Relative Index) and SFR (Simple Fluorescence Ratio) from the Multiplex® Research fluorometer (MP) in 2012 showed significant correlations with yield (Adj. $r^2 \leq 0.63$), and the NDVI (Normalised Difference Vegetation Index) and OSAVI (Optimized Soil-Adjusted Vegetation Index) of the FieldSpec HandHeld sensor (FS) even higher correlations with an Adj. $r^2 \leq 0.67$. Concerning the available N (N_{avail}), the REIP (Red-Edge Inflection Point) and CropSpec indices from the FS sensor had a high correlation (Adj. $r^2 \leq 0.86$), while the MP ratio SFR was slightly lower (Adj. $r^2 \leq 0.67$). Concerning the biomass weight, the REIP and SAVI indices had an Adj. $r^2 \leq 0.78$, and the FERARI and SFR ratios an Adj. $r^2 \leq 0.85$. The indices of the HandySpec Field® spectrometer gave a lower significance level than the FS sensor, and lower correlations (Adj. $r^2 \leq 0.64$) over all field measurements. The features of MP and FS sensor have been used to create a feature fusion model. A developed linear model for site-year 4 has been used for evaluating the rest of the data sets. The used model did not correlate on a significant de novo level but by changing only one parameter, it resulted in a significant correlation. The data analysis reveals that by increasing mixed features from different sensors in a model, the higher and more robust the r^2 values became. New advanced algorithms, in combination with existent map overlay approaches, have the potential of complete and weighted decision fusion, to ensure the maximum yield for each specific field condition.

Keywords: precision farming; sensor fusion; remote sensing; fluorescence; reflectance; spectrometry; nitrogen fertilisation; wheat; yield

1. Introduction

Agricultural systems using Precision Farming (PF) technologies have already been introduced in the market. The range varies from entry level guidance to data acquisition systems integrated into the farm management software. Most of these systems gather tractor-implement information, or perform tailor made applications [1]. The more intensive the crop production system is, the more advanced the technology adaptation on farms is [2]. This serves the goal of higher yields and better crop quality, with the support of sensor systems. The increasing number of available sensors, along with the high diversity of sensor technologies, e.g., imaging sensors, multi- and hyperspectral optical sensors, fluorometers, etc., has increased the possibility for integrating these sensor systems into the daily farm operation. Each sensor has advantages and disadvantages, and can provide important information concerning the field status [2–4]. Yet each sensor type has limitations to overcome. By merging the data of different sensors and sensor types, their limitations can be reduced, since data can be complementary or more informative [5]. In that sense, data fusion approaches are necessary, achieving better results by merging numerous sensor data deriving from the field and comparing them with ground truth data like yield or biomass.

Hall and Llinas [6] defined data fusion as "the integration of information from multiple sources to produce specific and comprehensive unified data about an entity". Brooks and Iyengar [5] classified four categories for sensor data fusion: (1) redundant; (2) complementary; (3) coordinated; or (4) independent fusion. Dasarathy [7] defined three levels: (I) raw data fusion; (II) feature fusion with feature extraction; and (III) decision fusion, which includes inter alia weighted decision methods [8]. Many different terms are used in literature to describe and discuss "fusion" concerning data. Dasarathy [9] also decided to use "information fusion" instead, as the overall term. In all cases, fusion of the sensor information can improve our knowledge of the field conditions [6].

For agricultural applications many sensors have been proposed. Several research studies based on spectral data are available, e.g., using data mining techniques with a genetic algorithm for nitrogen (N) status and grain yield estimation [10], or acquiring multispectral aerial images for the detection of wheat crop and weeds [11]. They are often based on measurements with one single sensor. There is a lack of information, of how informative different sensors and combination of sensors are, in the variability presented at the field level. Peteinatos et al. [12] measured stress levels in outdoor wheat pots with three optical sensors. Yet there is work to be done, connecting ground data with aerial data, even more in real field conditions. Using mobile platforms for data acquisition offers the possibility of system automation with fusion approaches. The advantage of ground platforms is their ability of carrying higher loads and more equipment than it would be possible with Unmanned Aerial Vehicles (UAV) [13].

In the current paper, the investigated research fields were planted with winter wheat utilising different N levels. These fields were examined with a fluorescence sensor and spectrometers, one spectrometer installed on an UAV, the other two spectrometers and the fluorescence sensor on a ground platform. The aim of this research was to test research sensors on field trails close to normal, practical farming conditions. This publication will discuss redundant and complementary fusion approaches, on a raw data and feature fusion level. It investigates the questions; (i) how the used research sensors perform in a large field; (ii) which of the calculated features are statistically significant for assessments of wheat yield, biomass and the available N for the plant; and (iii) how information fusion can support farming decisions.

2. Material and Methods

2.1. Experimental Site

The investigations have been made at the facility Ihinger Hof in Renningen (Germany), an institution of the University of Hohenheim, Stuttgart in South-West Germany. The location of

Ihinger Hof (N 48°44′41″, E 8°55′26″) has a mean annual precipitation of 690 mm (710 mm in 2011 and 727 mm in 2012), and an average annual temperature of 7.9 °C. The measurements about four site-years have been carried out with winter wheat (*Triticum aestivum* L., cv. Toras and Schamane) on the experimental fields "Inneres Täle" in 2011 respectively site-year (1), "Riech" in 2011 and 2012 (2) + (3), as well as "Lammwirt" in 2012 (4). The term "site-year" is a combination of two factors site and year, according to Beres et al. [14], where site relates to an individual field of a farm.

On site-year 1 and 4, the N levels ranged from 60 to 180 kg N·ha^{-1} in five distinct levels. Additionally a dosage of 170 kg N·ha^{-1}, that is usually applied on this farm, were used as the conventional application level. Figure 1 represents the N levels of site-year 1; site-year 4 had the same levels. Nitrogen was distributed in three fertiliser applications in the early growing periods (Zadoks' Scale (Z) 27–Z 47) [15] with a pneumatic fertiliser spreader and a tractor with an automatic steering system and GPS Real-Time Kinematic (RTK) precision (approx. ±2.5 cm). The first N application of 60 kg N·ha^{-1} has been distributed equally over the whole field. The second application had 0–80 kg N·ha^{-1} based on the treatment; and the third application has been carried out with 0–40 kg·N ha^{-1} to reach the planned total amount of N for the respective N level.

For site-year 2 + 3, the fertilisation was applied in repeating rows over the whole field: (1) control; (2) APOLLO model output [16]; and (3) Yara N-sensor control. The field design in this case was different compared to site-year 1 and 4, however it provided the required randomisation for the data analysis, with N levels from 60–170 kg N·ha^{-1} in eight distinct levels (see Figure 2).

Figure 1. The colored plots reflect the different N levels in kg N·ha^{-1} for site-year 1, as shown in the legend. Each plot has a size of 36 m × 12 m (L × W).
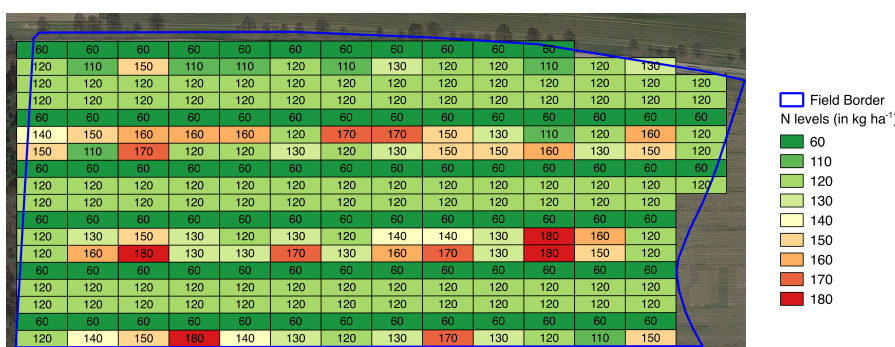

Figure 2. The colored plots reflect the different N levels for site-years 2 and 3, as shown in the legend. Each plot has a size of 36 m × 12 m (L × W).

Table 1 gives an overview of the site characteristics for the research fields. The research fields at the location Ihinger Hof have a high, natural field variability with soil types reaching from pure clay to silty loam. All fields of the location Ihinger Hof were investigated in the year 2009 on their electrical soil conductivity with an EM38 sensor (Geonics Limited, Mississauga, ON, Canada).

Table 1. Site characteristics for winter wheat (*Triticum aestivum* L.): plant density (No.·m^{-2}), seeding and harvest dates, and electrical soil conductivity (mS), of the three research fields Inneres Täle (IT), Riech (RI) and Lammwirt (LW) at experimental site Ihinger Hof, Renningen (Germany). C = Corn, WW = Winter wheat, OSR = Oilseed rape, T = Toras, S = Schamane, SD = Standard deviation.

Site-Year	Site	Year	Previous Crop	Variety	Plant Density	Seeding Date	Harvesting Date	Soil Conductivity			
								Min	Mean	Max	SD
1	IT	2011	C	T	340	27 November 2010	11 August 2011	19.68	38.19	56.98	4.93
2	RI	2011	WW	S	300	14 October 2010	4 August 2011	14.48	31.82	69.53	6.01
3	RI	2012	WW	S	300	17 October 2011	31 July 2012	14.48	31.82	69.53	6.01
4	LW	2012	OSR	T	300	14 October 2011	1 August 2012	52.49	64.48	85.57	6.38

On all four site-years, biomass (BM) samples have been collected over the whole field at three growing stages: stem elongation (approx. Z 35), flowering (approx. Z 61), and before harvest (approx. Z 93). To determine the N content in the soil (N$_{min}$-method), the samples were analysed on three soil depths: (1) 0–30 cm; (2) 30–60 cm; and (3) 60–90 cm. This took place at the end of tillering (Z 29) and after the harvest. The BM samples have been analysed for grains per ear, the number of tillers, the protein content and the BM weight. The wheat fields have been harvested with a standard New Holland combine harvester, equipped with a header of 6 m cutting width and a GPS receiver with RTK precision to geo-reference the yield data. The laboratory analysis and the yield logging are considered in the current manuscript as the ground truth data, with which the sensor data will be compared. The available N for the plant (N$_{avail}$), used in this manuscript, is defined as the sum of N$_{min}$ and applied N until the respective sensor measurement date. N$_{avail}$ is a simplified form to express the N supply for the plants in field, as atmospheric entries and mineralisation may provide additional N during the growing season. In spring, soil samples over the whole field have been taken and after harvesting. Table 2 gives an overview of the measurement dates for the ground and UAV mounted sensors for site-year 1. A similar frequency of the field sampling applies to the rest of the site-years.

Table 2. Exemplary for the other site-years, the overview shows the dates for site-year 1 (2011) regarding ground and aerial sampling in the different growing stages (Z). A = aerial spectrometer, G = ground spectrometer.

Z	Spectrometer	Fluorescence Sensor
30	G: 28 April 2011	28 April 2011
37	A + G: 20 May 2011	20 May 2011
75	G: 16 June 2011	16 June 2011
77	G: 28 June 2011	28 June 2011
85	A: 4 July 2011, G: 6 July 2011	6 July 2011

2.2. Measurement Set-Up

The sensor measurements derive from data of three sensors, two spectrometer devices, FieldSpec Handheld (FS—Analytical Spectral Devices, Boulder, CO, USA), HandySpec Field® (HS—tec5 AG, Oberursel, Germany), and the fluorescence sensor Multiplex® Research (MP—Force-A, Orsay, France). The ground sensors (Table 3) were mounted on a rebuilt self propelled Hege 76 multi-equipment carrier (Wintersteiger AG, Ried, Austria), the so called Hohenheim multi-sensor platform "Sensicle"; for more information and image see Keller et al. [3] and Zecha et al. [4]. The sensors mounted to the Sensicle have been adjusted at every measurement date at a specific height for each sensor relative to the canopy (Table 3). The spectrometers are passive sensors, highly dependent on the sun illumination. On the

other hand, the MP fluorometer is insensitive to the ambient light conditions due to its light-emitting diodes (LEDs) used for signal excitation. More information about the sensors can be found in Table 3.

Table 3. Used sensor devices and sensor details. BGF = Blue-Green Fluorescence; RF = Red Fluorescence; FRF = Far-Red Fluorescence.

Type	Manufacturer	Sensor Model	Wavelength Range	Spectral Resolution	Footprint	Classification
Spectrometry	Analytical Spectral Devices	FieldSpec Handheld	325–1075 nm	1 nm	2.74 m^2	Passive, Ground
	tec5 AG	HandySpec Field®	360–1000 nm	10 nm	0.44 m^2	Passive; Ground
	Carl Zeiss Jena GmbH & tec5 AG	MMS1 NIR enhanced	310–1110 nm	3.3 nm	50.27 m^2	Passive, Aerial
Fluorescence	Force-A	Multiplex® Research	BGF, RF and FRF	–	0.005 m^2	Active, Ground

The Monolithic Miniature-Spectrometer (MMS) 1 NIR enhanced (Carl Zeiss Jena GmbH, Jena, Germany & tec5 AG, Oberursel, Germany) has been selected due to the compact dimension, the low weight of only 500 g, and the high spectral resolution [17]. It has similar technical properties like the HS sensor mounted on the Sensicle ground platform (Table 3). It was mounted in the centre of a fixed-wing UAV pointing with the detector to the ground and set to a flight altitude of 100 m above ground; for more information and images see Link et al. [17].

2.3. Information Fusion and Statistical Data Analysis

The ground sensor software for triggering the measurements has been developed by the respective sensor hardware companies. The data logging software for the aerial spectrometer has been developed in C++ for Windows mobile 5 on a Personal Digital Assistant (PDA) [17]. The sensor raw data have been processed and converted to features (indices and ratios) that correlate with field information and biological parameters. This has been done using `Unix-Shell` and `awk` scripts on Ubuntu 12.04 Long Term Support, in combination with the statistical software `R` [18]. For the spectral data, several indices were derived, allowing a comparison with other sensor data. Common plant characteristics like the chlorophyll content, are commonly used to determine the presence of stress or correlate with the field biomass [19,20]. In the current measurements, the following indices were calculated:

Red-Edge Inflection Point [21]

$$REIP = 700 + 40 \times \frac{(R_{670} + R_{780})/2 - R_{700}}{R_{740} - R_{700}} \tag{1}$$

Normalised Difference Vegetation Index [22]

$$NDVI = \frac{(R_{780} - R_{680})}{(R_{780} + R_{680})} \tag{2}$$

CropSpec [23]

$$CropSpec = (\frac{R_{808}}{R_{735}} - 1) \times 100 \tag{3}$$

Hyperspectral Vegetation Index e.g., [24]

$$HVI = \frac{R_{750}}{R_{700}} \tag{4}$$

Optimised Soil-Adjusted Vegetation Index [25,26]—factor *L* varies between 0 and 1

$$OSAVI/SAVI = \frac{(R_{800} - R_{670})}{(R_{800} + R_{670} + L)} \times (1 + L) \tag{5}$$

For our analysis, a specific *L* value (canopy background adjustment factor) was used, 0.16 for OSAVI and 0.20 for SAVI. Concerning the Multiplex® Research fluorescence sensor, the following signals and ratios were used, as described in Cerovic et al. [27] and Ghozlen et al. [28]. The index denotes the fluorescence type while the subindex denotes the wavelength excitation of the LEDs:

$BGF_{UV/G}$ = Yellow Fluorescence
$RF_{UV/G}$ = Red Fluorescence
$FRF_{R/G}$ = Far-Red Fluorescence

Anthocyanins

$$ANTH = \log\left(\frac{FRF_R}{FRF_G}\right) \tag{6}$$

Flavonols

$$FLAV = \log(FER_{RUV}) \tag{7}$$

Fluorescence Excitation Ratio Anthocyanin Relative Index

$$FERARI = \log\left(\frac{5000}{FRF_R}\right) \tag{8}$$

Simple Fluorescence or Chlorophyll Ratio

$$SFR_{R/G} = \frac{FRF_{R/G}}{RF_{R/G}} \tag{9}$$

The geographic information system (GIS) Quantum GIS [29] has been used for data visualisation and for merging the geo-referenced features in form of indices, signals and ratios with the field design. Linear regression, analysis of variance (ANOVA) and branch-and-bound algorithm have been employed to the sensor data features with the aid of R. After post-processing the data, all features (independent variables—IDV) have been intensively analysed and correlated against the ground truth data (dependent variables—DV).

3. Results

3.1. Field Conditions

The average yield amounts of all site-years per N level are presented in Table 4.

Table 4. Average grain yield (t·ha^{-1}) for winter wheat (*Triticum aestivum* L.) with 14% grain moisture content at the different N levels (kg·ha^{-1}) of the four site-years.

Site-Year	Yield for N Levels					
	60	90	120	150	170	180
1	7.2	6.7	6.7	7.1	7.3	7.3
2	4.9	-	4.9	5.4	5.3	5.9
3	6.5	-	6.3	6.6	6.9	6.6
4	6.2	6.5	7.5	7.8	7.9	7.9

For the six N levels of site-year 1, yield showed an increasing amount with more N, except for the N level of 60 kg·ha^{-1} (Table 4). The 60 kg·ha^{-1} plots had a similar yield than the plots at a higher

N level. On site-year 4, the average yield increased with the N levels until the level of 150 kg·ha^{-1}. For the treatments of 150–180 kg·ha^{-1}, the yield remained on a similar amount. For site-years 2 and 3, these fields have been fertilised with a different strategy, so the average yield amounts per N level are not directly comparable to site-years 1 and 4. As shown in Table 1, all fields used in this research have a high deviation for the electrical soil conductivity with values ranging from 14.48 to 85.57 Milli-Siemens (mS). The field belonging to site-year 2 and 3 has the highest range of all investigated fields.

3.2. Regression Analysis

The feature extraction of the sensor raw data, presented as wavelength indices and fluorescence ratios, have been taken as independent variables (IDV) for the linear regression. As dependent variables (DV) for the following results have been chosen: (1) wheat yield; (2) BM weight; (3) leaf area index (LAI); and (4) available N (N_{avail}). The data analysis was carried out separately for each measurement date, to better observe the changes in correlation over time.

The linear regression results of the aerial sensor MMS1 data with the IDV's of site-years 2 and 3 are shown in Table 5. These results were not significant for DV's (1) and (3) of site-years 2 and 3, whereas DV LAI showed low correlations for site-year 2. The correlations with the DV's BM and LAI could not be measured for site-year 3. The number of valid UAV data fitting to the design layout of site-years 1 and 4 was too low for a significant data analysis.

Table 5. Linear regression analysis of UAV MMS1 sensor indices for site-years 2 and 3. Z = Zadoks' Scale, DV = Dependent Variable, IDV = Independent Variable, RMSE = Root mean square error, BM = Biomass, LAI = Leaf Area Index, HVI = Hyperspectral Vegetation Index, OSAVI = Optimized Soil-Adjusted Vegetation Index, REIP = Red-Edge Inflection Point, PVR = Plant Vigor Ratio, TCARI = Transformed Chlorophyll Absorption Reflectance Index.

Season	Z	DV	IDV	Adj. r^2	RMSE	*p*-Value
	73		HVI	0.15	0.31	0.0144
	73	LAI	NDVI	0.24	0.30	0.0020
	73		OSAVI	0.23	0.30	0.0024
	73		REIP	0.18	0.31	0.0077
	66		HVI	0.13	1521.64	0.0000
2011	73		HVI	0.21	852.72	0.0039
	34		NDVI	0.22	794.57	0.0246
	73	BM Weight	NDVI	0.23	838.76	0.0022
	34		OSAVI	0.22	793.42	0.0240
	73		OSAVI	0.23	842.12	0.0025
	34		PVR	0.19	812.01	0.0374
	73		REIP	0.17	875.04	0.0095
	61		REIP	0.09	0.47	0.0153
	85		NDVIg	0.08	0.49	0.0286
2012	85	LAI	HNDVI	0.08	0.49	0.0304
	85		OSAVI	0.07	0.49	0.0315
	85		NDVI	0.07	0.49	0.0332
	61	BM Weight	TCARI	0.08	117.17	0.0229

Tables 6 and 7 present the correlation results of site-year 4 for the ground sensors MP and FS, only for Adj. r^2 values > 0.46. The FERARI and SFR ratios are significant with yield and BM weight for end of heading and flowering growing stages onwards; the Yellow Fluorescence (BGF) correlates already at the beginning of stem elongation. For N_{avail}, the SFR ratio and the RF signal show significant results (Table 6). The calculated indices HVI, NDVI, OSAVI of the FS sensor show correlations with yield over several measurements of the growing season. The CropSpec and REIP indices highly correlate with N_{avail} for the end of heading stage and further on, HVI and NDVI on the other hand have a lower correlation (Table 7).

Table 6. Linear regression analysis of signals and ratios from Multiplex® Research fluorescence sensor for site-year 4. Z = Zadoks' Scale, DV = Dependent Variable, IDV = Independent Variable, RMSE = Root mean square error, BM = Biomass, FERARI = Fluorescence Excitation Ratio Anthocyanin Relative Index, SFR = Simple Fluorescence Ratio, BGF = Yellow Fluorescence. Significance level: *p*-value < 0.001.

Z	DV	IDV	Adj. r^2	RMSE
66		FERARI	0.48	0.75
85		FERARI	0.49	0.74
59	Yield	SFR_G	0.53	0.71
85		SFR_G	0.61	0.65
59		SFR_R	0.56	0.69
85		SFR_R	0.63	0.64
59	N_{avail}	SFR_G	0.67	16.52
66		RF_{UV}	0.63	26.77
31		BGF_G	0.46	97.66
59		BGF_G	0.61	83.32
85		BGF_G	0.73	69.21
91		BGF_G	0.74	68.11
85	BM Weight	FERARI	0.83	55.25
85		FLAV	0.62	81.98
85		FRF_R	0.86	50.40
85		RF_G	0.83	54.91
85		SFR_R	0.85	52.14

Table 7. Linear regression analysis of indices from spectrometer FieldSpec HandHeld for site-year 4. Z = Zadoks' Scale, DV = Dependent Variable, IDV = Independent Variable, RMSE = Root mean square error, BM = Biomass. Significance level: *p*-value < 0.001.

Z	DV	IDV	Adj. r^2	RMSE
59		HVI	0.56	0.68
66		HVI	0.54	0.70
85		HVI	0.59	0.65
66		NDVI	0.56	0.70
85	Yield	NDVI	0.63	0.62
59		OSAVI	0.55	0.69
85		OSAVI	0.67	0.58
85		REIP	0.54	0.69
85		CropSpec	0.53	0.70
59		CropSpec	0.79	13.12
66		CropSpec	0.68	24.57
85		CropSpec	0.78	20.56
59		HVI	0.69	15.98
66		HVI	0.67	25.08
85	N_{avail}	HVI	0.68	24.78
66		NDVI	0.62	27.15
85		NDVI	0.62	26.91
59		REIP	0.86	10.76
66		REIP	0.76	21.40
85		REIP	0.83	18.04
31	BM Weight	REIP	0.78	67.07
85		SAVI	0.75	67.22

3.3. Data Validation

Basis of the data validation were the results of Zecha et al. [4], in which four mixed correlation models were presented, based on measurements with the same spectral and fluorescence sensors. From this research, Model 4 is proposed by the authors for cross-validation with the sensor data of site-years 1–3. The parameters A_x, B_x, C_x and D_x denominate the modelled coefficients of the linear regression—Model 4 as shown in [4]:

$$y = A_4 + B_4 \times CropSpec + C_4 \times HVI + D_4 \times RF_{\text{UV}} \tag{10}$$

By cross-validating the above model with the data from site-years 1–3, the correlations were low. Using a Find-Best-Model-Algorithm in R for the data sets of all site-years, the following yield model has been discovered:

$$Yield_{predicted} = A_x + B_x \times FERARI + C_x \times HVI + D_x \times RF_{\text{UV}} \tag{11}$$

Table 8 highlights the corresponding correlations for Model 4 of site-year 4 and for the new model $Yield_{predicted}$, employed to the data sets of all site-years.

Table 8. Adj. r^2 values of Model 4 and model $Yield_{predicted}$ for the corresponding FS indices and MP signal, grouped by months and site-years. n.a. = not available, n.s. = not significant. p-values for Model 4 < 0.05. p-values for $Yield_{predicted}$ < 0.001.

Model	Site-Year	April	May	June	July
Model 4	4	0.52	0.52 + 0.79	0.75 + 0.77	0.20
	1	0.18	0.24	0.40 + 0.47	0.47
$Yield_{predicted}$	2	0.17	n.a.	0.32	0.37
	3	n.s.	0.31	0.40	0.39
	4	0.26 + 0.40	0.50 + 0.71	0.64 + 0.74	0.66

4. Discussion

This study describes the performance of the used optical sensors, and their ability of wheat yield, biomass and N_{avail} assessment. Based on the yield amounts, the crop development had a steady growth for all site-years, despite of an irregular high yield amount of site-year 1 at the field plots with an N level of 60 kg·ha^{-1}. The reason for this irregularity may be caused by the previous season in 2010. There, corn was planted which can have positive effects on the organic humus content of the field, e.g., Singh Brar et al. [30]. For site-years 1 and 4, the yield at N levels between 150 an 180 kg N·ha^{-1} had no increasing effect on the grain quantity or quality [4]. A lower N level can be recommended for the fertiliser management of these fields for the cultivation of wheat. The total average yield of site-year 3 was 26.7% higher than on site-year 2, which is an indication of more BM in the field, that is able to produce more grain.

The UAV MMS1 spectrometer has similar technical properties like the HS spectrometer, however, the results of both sensors are on a different prediction level for the IDV's in the presented research design. The analysis with the chosen DV's yield and N_{avail} for the MMS1 spectrometer data did not show any correlations. For site-year 2, there are low correlations for BM Weight and LAI; they were not repeatable for site-year 3 (Table 5). Reasons for the low or non existent correlations, based on the findings of Link et al. [17], are (1) a limited path accuracy with the consequence of outlaying data points not fitting to the research field design; (2) height inaccuracy of the UAV; (3) a short flight time of 15 min which required several flight missions to cover the entire research field; (4) that data post processing relies on accurate data from the autopilot system for pitch and roll correction of each data point, and on the control measurement of the MMS1 sensor at the start of the UAV. As the sensor in this setup only could be configured for continuous measurements, a lot of the logged data were of no use as they included the necessary flight turns and the surface measurements on the flight to the research field, Changing light conditions during the following flight mission affected the measurement precision in each design plot; and (5) the sensor footprint of 50.27 m^2 with an overlapping factor of 0.33 [17], covering a larger area at each measurement than the ground sensors were able to acquire (Table 3). As a consequence, the MMS1 data had a higher averaged value than the ground sensor data, which results in a lower resolution and a lower detection accuracy. However, this may be sufficient

depending on other investigation purposes, ensuring a stable flight altitude and an integrated fusion approach on a raw data or feature fusion level. Other aerial platform approaches, like an electric multicopter, may lead to better results due to its better flight stability and easier point to point navigation behaviour. Geipel et al. [31] took the same MMS1 spectrometer like in the presented manuscript and mounted it to a hexacopter. With the same ground-truth information via sampling the above-ground BM they were able to measure higher correlations with BM and grain yield, taking into account a data acquisition system for all involved sensors [32].

The MP fluorometer was able to detect significant correlations with grain yield (Adj. r^2 of 0.48–0.63), notably in the ratios SFR with green and red excitation as well as in FERARI. They are linked to the chlorophyll content of the crop [33,34]. The correlations with the available N are high and reach Adj. r^2 values of 0.63–0.67 at a later growing stage (Z 59 and Z 66) with the RF signal and the SFR ratio. The highest correlations are with BM related properties. The correlations with the BM weight range from an Adj. r^2 of 0.46 at the early growing stage (Z 31), up to an Adj. r^2 of 0.86 at ripening (Z 85) and senescence (Z 91) stages. Fluorescence sensors for agricultural usage on tractors or other mobile platforms are barely in use. Their required contact with the crop canopy is one of the reasons why most of the used agricultural sensors are based on spectral characteristics [35]. However, due to the active LED emission source of the MP sensor, it provides a profound, reliable and repeatable technology especially for measurements on the field with changing illumination. Hyperspectral line scanners do not require close contact with the crop canopy and use sun induced fluorescence, however their field application is still in discussion and used on a research level [36].

Spectral sensors are already well adopted at large modern farms, and are able to fuse the measured data with previously gathered data sets via a map overlay approach [2,37,38]. Also in scientific research spectral sensors have a high acceptance, as more than 90% of the spectral information on crop canopy is contained in the red and near infrared (NIR) spectral bands [39,40]. For the FS indices HVI, NDVI, OSAVI, REIP and CropSpec, the correlations with yield increased, starting at heading stage (Z 51) to a high level of an Adj. $r^2 = 0.67$ at ripening stage (Z 85). Especially the indices CropSpec and REIP correlate very high with N_{avail} and provide an Adj. r^2 up to 0.86. For the BM characteristics, REIP, SAVI and CropSpec have high Adj. r^2 values > 0.63 already from stem elongation stage onwards (Z 30). The r^2 values of the HandySpec sensor data analysis was at a lower level than the ones from the FieldSpec sensor. They conclude in a maximum correlation of an Adj. $r^2 \leq 0.64$ at a significance level <0.05, with the presented DV's and IDV's.

For research, the high correlations of the MP fluorometer and the FS sensor can be merged on a feature fusion level. This has been done by Zecha et al. [4] and in the presented manuscript with a data post-processing method. The developed Model 4 from site-year 4 has been applied to the data sets of site-years 1–3. Model 4 did not correlate on a significant level with the gathered sensor data in these three site-years. However, a similar combination of indices and ratios (model *Yield_{predicted}*) resulted in significant correlations for all four site-years, by changing only one parameter (FERARI with CropSpec). By this change, the Adj. r^2 was between 0.32 and 0.74 two months before harvest for all site-years. The data analysis reveals that the more mixed indices and ratios are in a model, the higher and more robust the Adj. r^2 values became, like RF_{UV} and HVI, combined with index CropSpec or ratio FERARI, in the investigated linear models.

This model has a potential to continue working. Three out of the four parameters are exactly the same, providing results for the other three site-years. On the other hand, the ability of the presented model, predicting wheat yield by using unknown or different data, has not yet been validated, e.g., with machine learning methods proposed by Peña et al. [41] or as comparison with the linear models of Mortensen et al. [42] estimating above-ground biomass and N-uptake through aerial images. Future work needs to be done to train and test the real capabilities of this model, and to prove if it works.

5. Conclusions

(i)   The used aerial data collection system, as a combination of a fixed wing UAV and the MMS1 spectrometer, cannot be recommended for multispectral data acquisition like it has been done in the presented setup. A limited path accuracy, a short flight time of approx. 15 min including take-off, flight turns and landing, the MMS1 sensor setup in continuous measurement mode, independent sensor data logging and the related huge post-processing efforts, and the footprint along with an overlap of 30% make it unfavorable for a qualitative data analysis and feature correlation with ground truth data. For the aerial data acquisition, the authors recommend an integrated data acquisition system with all sensors connected via a sensor data infrastructure.

(ii)   Two ground sensors mounted to the Sensicle platform, the fluorometer Multiplex® Research (MP) and the FieldSpec HandHeld (FS) spectrometer, had high correlations with wheat yield, available nitrogen and the sampled biomass characteristics from the field plots. The HandySpec Field® (HS) spectrometer had lower significant correlations in all site-year than the FS sensor. The usage of the three ground sensors in continuous measurement mode is most reliable for the fluorometer MP. With an internal GPS sensor and an active LED source, measurement starts with one click and data storage on a SD card. The FS and HS spectrometer require an additional device for measurement triggering, and do rely on an external GPS receiver. The raw data post-processing cannot be handled without scripts, converting the raw data in features like indices, while calculating them with the white reference measurements, taken at the start of each continuous measurement series. The ability of the presented model, predicting wheat yield by using unknown or future data, has not yet been validated. Recommending the developed model for a general performance, further model training and model testing need to take place.

(iii)   An enhanced algorithm during the raw data calculation of the spectrometer, taking into account the ambient solar radiation during each continuous measurement mission, may improve the correlations and make the developed model more robust to apply it in earlier growing stages with high correlations. Advanced algorithms considering the factors (1) ambient solar radiation; (2) electrical soil conductivity; (3) aerial images with feature extraction; or (4) soil scoring may result in better yield predictions by providing the right decision for each spot in a field. In combination with the existent map overlay approaches of today's spectral sensor systems, these complete and weighted decision can save field inputs and ensure the perfect crop development to reach the maximum yield for the specific field. Once, the field data collection and analysis process can be accomplished with sensors and software in an convenient way also for a farmer, the adoption of sensor technology in agriculture will increase.

Conflicts of Interest: The authors declare no conflict of interest.

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5 Discussion

This thesis is based on measurement analysis from different optical sensors in parallel usage on a ground and an aerial sensor platform, to investigate the performance of sensors in large field trails for yield prediction and biomass (BM) characteristics detection. It used for the first time the Multiplex® Research (MP) fluorescence sensor for measurements in wheat fields. The aims of this thesis were the (i) evaluation of different, available sensors and sensor platforms used in Precision Farming (PF) for quantifying the crop nutrition status, (ii) acquisition of ground and aerial sensor data with two ground spectrometers, an aerial spectrometer and a fluorescence sensor, (iii) development of effective post-processing methods for correction of the sensor data, (iv) analysis and evaluation of the sensors with regard to the mapping of BM, yield and nitrogen (N) content in the plant, and (v) yield simulation as a function of different sensor signals. The following discussion intends to interpret the five working goals and findings, and gives an outline for future sensor systems in PF.

5.1 Aerial and Ground Vehicles as Mobile Sensor Platforms

The conducted measurements with the ground sensor platform Sensicle and the fixed-wing unmanned aerial vehicle (UAV) were influenced by several factors. The sensors installed on both platforms for measurements in the research fields were exposed to (1) rough field conditions, (2) turbulences in the air, (3) dew on plants, (4) changes in the solar radiation, (5) changing distance to the desired measurement objects, (6) dimension restrictions, (7) self-shadowing, and (8) overlapping effects (Agogino et al., 1995; Schilling et al., 1996; Griepentrog et al., 2010; Schulz et al., 2012).

The spectral sensor MMS1 on the fixed-wing UAV was affected by the factors (2), (4), (5), (6) and (8), causing a high percentage of invalid sensor data. Reasons for these influencing factors are: The continuous measurement mode of the MMS1 data logging could not been triggered via a remote control, therefore the sensor stored data also at flight turns and during take-off and landing, with numerous measurements not spatially fitting to the design layout of the research fields. Through the limiting maximum take-off weight below 1.5 kg, it was not possible to implement an RTK radio enabling the UAV to do georeferencing with the same precision of $\pm$ 2.5 cm as on the Sensicle. The MMS1 data analysis was performed with the initial reference measurement taken before the UAV take-off (Link et al., 2013). An additional aerial spectral sensor for reference measurements of solar radiation during the flight mission can improve the spectral measurement results. In the air, the airplane rotates in three axis: pitch, yaw and roll. Two of the three dimension were majorly influencing the measurements: the pitch axis affecting the height, and the roll axis causing an angular displacement. Through the telemetry logs of the UAV autopilot, containing the necessary pitch and roll information along with the GPS data, the spectral sensor data were corrected to its real measurement position (Link et al., 2013). The sample size of the post-processed UAV sensor data from two site-years was too

low for a significant data analysis. On the two remaining site-years the sample size was right, however, the data analysis showed low correlations only for one site-year. Based on the experience derived from this thesis with the fixed-wing UAV, a multicopter UAV was considered as a more viable aerial platform, that allows for more precision in exact field trails conducted at Ihinger Hof and for a higher payload for additional sensors. The measurements with the MMS1 sensor continued with a rotary UAV (Geipel et al., 2014). Further investigations are done to fuse ground and aerial spectrometer data (Domingues Franceschini et al., 2017), using a hyperspectral mapping system (Suomalainen et al., 2014), and showing good estimates for canopy chlorophyll and ground cover, i.e., the biomass. This indicates a positive direction for UAV's being good platforms to gather sensor data without causing soil compaction or crop damages.

The Sensicle ground sensor platform, exclusively modified for the SENGIS research topics, offered a variety of mounting positions, almost without limitations regarding sensor weight and sensor dimensions. As an initial step, two spectrometers and a fluorescence sensor have been installed on a specific frame adjustable in height above canopy and width (distance to the tramline). For the setup of the Sensicle sensors, the factors (1), (3), (4) and (7) had to be considered, influencing the measurement time through wet crop canopy, the driving speed through frame vibrations, and the mounting position of each sensor depending on its type – active with own light emissions like the fluorescence sensor, or passive like the spectrometers without an own light source and the need for sufficient ambient light radiation. Additionally, a luxmeter was installed on the Sensicle for indications of radiation changes through clouds. In case of a radiation change, the Sensicle was stopped and a new sensor calibration measurement was done. The multi-sensor platform Sensicle is a versatile sensor carrier for mission sensors, and enables for testing of existing and new sensors in exact field trails and real field conditions. For new research scopes with the Sensicle and more sensors in parallel usage, a sensor infrastructure with an automated fusion algorithm is recommended, to reduce data acquisition time, and to further improve data and feature detection accuracy.

5.2 Sensor Data Quality in Precision Farming Applications

Non-destructive methods can derive targeted decisions for a particular application, such as a required site-specific amount of fertiliser per ha. Therefore, the time and GPS position correction of each sensor is crucial to ensure the exact spatial location of each measurement and application point. The cleansing of data, like the removal of outliers or irregularities in a data set, is an essential part to ensure a high data quality. This prevents algorithms of decision support systems to output overfitting or incorrect results. Precise ground-truth data, like the crop yield, is the key to good results by reducing the standard deviation (Blackmore, 1999; Thylén et al., 2000; Kleinjan et al., 2002).

The yield data of this study have been visualised with the program QGIS to detect field irregularities at the headland and the inner field, based on the field border and a satellite background image. The yield data set has been cleaned based on the harvester driving speed,

grain humidity, start and end track delays at the headland and full or part cutting width of the combine harvester header. Ground-truth data like protein content or BM weight were based on laboratory analysis. The spectrometer data were checked for clipping effects, i.e. overexposed values, with computer scripts and automatically cleaned. The corrected data sets needed to be transformed to a certain file format in order to analyse them with software programs for calculation, classification and modelling. These are time consuming tasks, requiring expertise in data evaluation and knowledge about decision criteria, and is a reason why this is hardly done in practical agricultural applications (e.g. Barwicki et al., 2015; Balafoutis et al., 2017). If the data quality is good, the resulting decision can have a significant effect in a field, by reducing the resource allocation while optimising or increasing the yield.

5.3 Field Characteristics Mapping with Sensors

Commercial optical sensors for N fertilisation do measurements based on spectral properties, e.g. calculate the decision about the necessary fertiliser amount based on chlorophyll reflectance (e.g. Gitelson et al., 2003). They can have a certain distance to the plant, detecting the reality in field better with a bigger footprint. The used sensors in this study have a footprint between 0.005 and 2.74 m^2 for the ground sensors and a footprint of 50.27 m^2 for the aerial sensor.

The measurements of the Sensicle and the fixed-wing UAV are offline approaches. The predictions for the N uptake of the plant were low for all sensors indices of this study. However, REIP and the SFR ratio showed high correlations with available N especially in June and July where the biomass is fully developed. For biomass weight, REIP and the index SAVI were significant; the ratios and signals of the MP fluorescence sensor were highly significant for BM weight. FERARI and SFR of the MP sensor showed significant results for yield.

To derive decisions, e.g. on the next fertiliser application amounts, it takes a certain processing time. Online sensor approaches are preferred for reacting immediately to variable and heterogeneous field conditions. This requires compatible data protocols like the ISOBUS (Auernhammer, 2001). Depending on the research topic, the used MP sensor, FieldSpec Hand-Held (FS) and HandySpec Field® (HS) sensors are capable of detecting features related to BM, yield and N content in the plant, while the FS sensor was more reliable than the HS sensor, resulting in higher correlations. The MP fluorescence sensor has an active light source that can compensate for the disadvantage of a spectrometer with regard to changing light radiation during a measurement mission.

5.4 Spatial Combination of Fluorescence and Reflectance Sensor Data

This study used offline post-processing methods, merging sensor data after data acquisition in a field by GPS position and GPS time. The sensor data were assigned to the research field design of every year with GPS RTK precision, i.e. $\pm$ 2.5 cm. The developed scripts for this

thesis are available for research projects with sensor data post-processing tasks. This enables for faster conversion from raw data to comparable features. Based on Dasarathy (1997), this study applied raw data fusion and feature level fusion; raw data fusion in regard to the sensor data conversion to indices and ratios, and feature level fusion through the signal combination in statistical linear models.

Optical sensors based on spectrometry or fluorescence for the connection to an agricultural machine are available. They are of particular interest to agriculture as they can determine multiple valuable parameters, like for example the nutritional state of a plant through non-destructive methods. The Yara N-Sensor®, the CLAAS CROP SENSOR i.e. the Fritzmeier ISARIA, or the Trimble® GreenSeeker® are examples (Reckleben, 2013). These sensors measure one of the indices NDVI, CropSpec or REIP, that is why special attention was paid to these indices and values in this study. A combination of different sensor signals can deliver a more robust and efficient prediction result, taking advantage of three possible sensor configurations: (i) competitive/redundant, (ii) complementary, or (iii) cooperative sensor configuration (Durrant-Whyte, 1988).

Through a combination of fluorescence signals and ratios (RF, FERARI and SFR) and spectrometer values (CropSpec, HVI, NDVI and REIP), linear models for the prediction of wheat yield were generated. The cross-validation of these linear models, containing different sensor signals, were correlating significantly over the vegetation periods of all site-years. The fusion of different sensor signals performs better than the signals of one sensor alone. The more mixed indices and ratios of different sensors are included in the developed statistical models, the more efficient and more robust the wheat yield could be simulated. Moeckel et al. (2017) did sonar and spectral variables fusion in grasslands. Yokoya et al. (2017) and Zeng et al. (2017) present fusion approaches for spectrometer and multispectral camera data. These authors and the study for this thesis prove successfully the advantages of sensor signal fusion for wheat and other crops with the same sensor technology.

5.5 Nitrogen Level Identification and Yield Prediction in Wheat with Ground and Aerial Sensors

Benedetti et al. (1993) and Raun et al. (2001) estimated wheat yield by NDVI measurements from a spectral sensor, explaining 83% of the measured grain yield variability. Tremblay et al. (2009) used a leafclip fluorescence device for prediction of wheat yield. A combination of both sensor technologies is barely in use.

For the yield prediction model analysis of this thesis, the RF signal, FERARI, the SFR ratio, REIP as well as the indices CropSpec, HVI and NDVI were chosen. Through a combination of fluorescence ratios and spectrometer indices, using a Find-Best-Model-Algorithm in R, linear models for the prediction of wheat yield were generated. The cross-validation showed, that there is a potential in the combination of sensor features like ratios from fluorometer data and indices from spectrometer data. The more mixed indices and ratios of different sensors

are included in the statistical models, the more efficient and more robust wheat yield can be simulated. The RF_{UV} signal and the HVI index, combined with the CropSpec index or FERARI, shall be further investigated in terms of yield simulation, as well as nitrogen level identification and BM characteristics.

The data analysis of this study reveals that the investigated linear models with mixed indices and ratios from different sensors have a higher and more robust correlation. For a future usage of this studies models, more training and testing of the real capabilities has to prove if it works, e.g. with machine learning methods proposed by Peña et al. (2014) or with comparing the linear models of Mortensen et al. (2015) estimating above-ground biomass and N uptake through aerial images.

5.6 Vision for Sensor Systems in Precision Farming

In recent years, small single-board computers like the Raspberry Pi (Raspberry Pi Foundation, Caldecote, Cambridgeshire, UK) were launched on the market. They enabled new approaches and methods for field applications. Through low energy consumption, small size, high processing power and Open-source system software, they are capable for connecting multiple sensors, taking into account fusion algorithms. Geipel et al. (2015) propose a data acquisition system that connects the sensors used in this study with a Raspberry Pi. Approaches like this may help to enhance agricultural applications with inexpensive sensors. Future applications in agriculture will have a strong need for mobile sensor platforms involving ground and aerial vehicles.

Collaboration between agricultural machine manufacturers, sensor providers, as well as seed and chemical companies provide sensor measurements as map layer services for farm management information systems (FMIS). These FMIS' enable farmers to use resources like fertilizer or chemicals more efficiently, as they can preplan their field task as work orders for the machine. Work orders can contain the field boundary, the field name, obstacles, waylines and may include prescription maps with different application rates. Data collection in modern
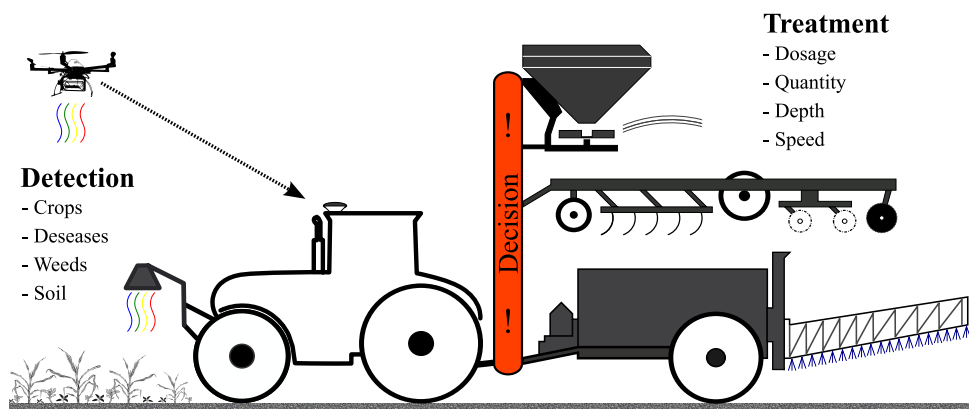

Figure 1: Sensor-Applicator-Systems in modern agriculture with external aerial data source for a preplanned and online application, changed according to Zecha et al., 2013

agriculture is focused on attachments to a tractor or an implement. More operable systems for the farmer with direct decision support on the machine are desired approaches on modern farms. Through collaboration and industry standards like ISO 11783 (Miettinen et al., 2006), farmers can easier transfer data, connect multi-brand implements to a tractor and integrate compatible sensor technologies into their daily field operations (see Fig. 1). New standards for data transmission, e.g. low range Bluetooth, enable for a near realtime downstream of the gathered data. Agricultural machine manufacturers are working on Machine to Machine communication for in-field working groups. With new data transfer technologies also Machine to Drone communication are in focus, to incorporate more valuable data.

More robust sensor solutions with higher reliability will become available for agricultural decision-making, providing more sensor data (Adamchuk et al., 2010). Combining large scale data, e.g. from a UAV, with detailed point data from a ground-based vehicle, offer a wider range of measurement values within a shorter time period. Until a tractor-sensor combination enables an easy data collection and decision support for multiple sensors with an affordable pay back time for farmers, multi-sensor systems for data acquisition and decision support may be offered as a farm advisory or an agronomist service. Therefore, on the one hand, easy to use decision support systems for the operator or farmer are necessary. On the other hand, more standardised system components are required.

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Publications

The following sections list all peer-reviewed and non-peer-reviewed publications associated with this dissertation.

Peer-reviewed publications

Zecha, Christoph W., Gerassimos G. Peteinatos, Johanna Link, and Wilhelm Claupein (2018). Utilisation of Ground and Airborne Optical Sensors for Nitrogen Level Identification and Yield Prediction in Wheat. In: *Agriculture*, 8, 79.

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Non-peer-reviewed publications

Zecha, Christoph, Johanna Link-Dolezal, and Wilhelm Claupein (2013). Nährstoffdefizite erkennen – Fluoreszenz und Spektrometrie im Vergleich. In: *Mitteilungen der Gesellschaft für Pflanzenbauwissenschaften – Nachhaltige Erzeugung von Nachwachsenden Rohstoffen*. Ed. by B. Märländer, O. Christen, K. Dittert, K. H. Mühling, S. von Tiedemann, and A. Düker. Deutsche Gesellschaft für Pflanzenernährung e. V. Göttingen/Freising-Weihenstephan: Verlag Liddy Halm, Vol. 25, pp. 291–292.

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