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RESEARCH ARTICLE

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Optimizing precision agricultural operations by standardized cloud-based functions

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Abstract

Aim of study: An approach to integrate knowledge into the IT-infrastructure of precision agriculture (PA) is presented. The creation of operation relevant information is analyzed and explored to be processed by standardized web services and thereby to integrate external knowledge into PA. The target is to make knowledge integrable into any software solution.

Area of study: The data sampling took place at the Heidfeld Hof Research Station in Stuttgart, Germany.

Material and methods: This study follows the information science's idea to separate the process from data sampling into the final actuation through four steps: data, information, knowledge, and wisdom. The process from the data acquisition, over a professional data treatment to the actual application is analyzed by methods modelled in the Unified Modelling Language (UML) for two use-cases. It was further applied for a low altitude sensor in a PA operation; a data sampling by UAV represents the starting point.

Main results: For the implemented solution, the Web Processing Service (WPS) of the Open Geospatial Consortium (OGC) is proposed. This approach reflects the idea of a function as a service (FaaS), in order to develop a demand-driven and extensible solution for irregularly used functionalities. PA benefits, as on-farm processes are season oriented and a FaaS reflects the farm's variable demands over time by origin and extends the concept to offer external know-how for the integration into specific processes.

Research highlights: The standardized implementation of knowledge into PA software products helps to generate additional benefits for PA.

Additional key words: agricultural value chain; cloud computing; function as a service; precision agriculture; standardization; web processing service

Abbreviations used: API (Application Programming Interfaces); CAN (Controller Area Network); DIKW-model (data–information–knowledge–wisdom-model); DSS (Decision Support System); ExGR (excess green minus excess red index); FaaS (Function-as-a-Service); FMIS (farm management information system); GDPR (General Data Protection Regulation); http (hypertext transfer protocol); IoT (Internet of Things); ISOBUS (International Standardization Organization Binary Unit System); IT (information technology); OGC (Open Geospatial Consortium); PA (precision agriculture); PaaS (Platform-as-a-Service); RGB (red–green–blue); SOA (service-oriented architecture); UAV (unmanned aerial vehicles); UML (Unified Modelling Language); WFS (Web Feature Service); WPS (Web Processing Service); XML (extensible markup language).

Authors' contributions: Development of concept: MJ, GP, RG. Development of models and realization of infrastructure and web services: MJ. Gathering and processing of field data: RM, BK. Writing the original draft: MJ, GP, RM, RG.

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Introduction

Nowadays agriculture is highly mechanized and incorporates various sophisticated systems, technologies and sensors. For a successful agricultural practice, and in which one achieves the optimum result, it is imperative to establish the cooperation between the farmer and other actors, such as sensor and machinery manufacturers, chemical and ecological conductor vendors, relative advisory services and current knowledge and trends of the scientific community. An important aim of successful farming is to increase yield by modifying and optimizing the process to achieve the best possible environment, requiring the minimum effort, natural sources, and environmental load, while preserving and, if possible, increasing the product quality. Precision agriculture (PA), originally established in the 1980s has already delivered tools and technologies that are aiding agriculture. Satellite-guided systems, satellite-based data, spectral indices, drone data are readily available. Information technologies are pushing the development of new tools and ideas. Sensors are improving, while data gathering and transportation enable a better overview of the field. This result facilitates a more optimized field management and diversification. In moving towards that goal, data handling and relevant infrastructure need to be improved (Villa-Henriksen, 2020). Available data sometimes are not utilized, at least not to their full potential, due to the lack of integration means among different systems (Fulton, 2018). Hardware, software, data and services need to be established and incorporated in a unified environment.

The most distributed standard in agricultural field operations is the ISO 11783. The ISOBUS (International Standardization Organization Binary Unit System) was established as a unified communication protocol for tractors to implement and extend towards the farm management information system (FMIS). The tractor-implement system has been irreplaceable for the farmer. In addition to hardware-linkage, it defines the method, data-transfer format and user-interfaces. It designs the interface to the vehicle bus standard CAN (Controller Area Network). The relevance of ISOBUS has increased by the development of PA and the meaning of transparency with regards to agricultural production. In 2013, already 50% of tractor vehicles had the capability to be equipped with ISOBUS (Daróczi, 2013). In particular, for high-grade machinery it became a basic feature.

The widespread use of ISOBUS is an invitation and a deterrent at the same time. Its concept is powerful, but it is also complex. This complexity is expressed in the size of the belonging ISO 11783 standard, which consists of 14 parts. It is seldom realized to its full potential or specifications. The majority of implementations focus normally on their application. The integration of components on the machine, which do not belong to basic tractor equipment, is often insufficient. Even communication between different versions or generations of implements are often ambiguous. Integration, for example from additional field sensors, is a challenge for software developers. Concerning sensors, there is good implementation for established products (Paraforos *et al.*, 2019), but it might be hard to dock a new, innovative sensor and integrate its data into the information technology (IT)-system of the machine. Nikander *et al.* (2019) noticed an increasing number of farmers using software, but many of them work with printed operation maps in the field. The information chain from preparation at the desk by a farm management information system (FMIS) to the terminal screen is not seamless or trivial for farmers (Sørensen *et al.*, 2010). In particular, this is true when devices or software of different brands or ages have to interact. For several years, large sellers of machinery have offered web-based platforms for machinery data exchange. Wolfert *et al.* (2017) identified those as limited but observed a slow rethinking towards open data exchange by open Application Programming Interfaces (APIs). APIs might make big data analysis possible, as manufacturers noticed potential benefits from the agricultural value chain. A practical example is "Nevonex" (Robert Bosch GmbH, 2020), a platform including ISOBUS and non-ISOBUS devices by operation-oriented applications. Each feature on this platform offers individual functionalities, but also the option of exchange. It thereby makes the exchange of data from different PA components easier. Expandability becomes more straightforward, and it simplifies the development of new hardware and software.

The relevance of more information in field managing processes was evaluated by Dyer (2016), who explained this importance through the logic of better operations for more information. Furthermore, he gives an overview of efforts and strategies by companies into this field. On the other hand, Daróczi (2013) determinated that farmers could not benefit from additional data. Therefore, data have to be upgraded into operationally relevant information by procedures. External additional sources and sensors are themselves producing numbers without value. Further calculation (and knowledge) is needed to convert data into information about the situation at the location and time of measurement. This information might be useful for defining operations.

Daróczi (2013) recommended the interconnection and automation of processes in PA. Inspired by the work of Nash *et al.* (2009), who presented the idea of improving PA by integrating in it the standards of the Open Geospatial Consortium (OGC). Similarly, Kaivosoja *et al.* (2013) integrated the ISOBUS on the machine level by improving the functionality of the task controller using an OGC Web Feature Service (WFS). In doing so, the well-developed data handling of geoinformatics is connected to the standards of PA. The WFS-standard is one of the OpenGIS web services of the OGC. Among other OGC services the OGC Web Processing Service (WPS) is the service description for the realization of processing in a standardized way, implying the knowledge and logic of data processing.

Standardization makes integration into software solutions possible with low effort. Existing systems could be expanded by a WPS-interface, visible for the user or hidden behind the functionality of a software solution. As a service could be integrated into every service-oriented architecture (SOA), a desktop-based software, a web-client or a mobile app could interpret the WPS-logic and increase operation-range and -density.

Regarding the internet of things (IoT), processing of sampled data has a central meaning for future development, as the storage of data is not equal to an added value, rather it is information created from these data by processing by requests via hypertext transfer protocol (http) and responses in extensible markup language (XML). It was designed for geospatial applications but could be used for the processing of non-spatial data as well (Müller, 2018).

Kraatz *et al.* (2015) presented a use-case for PA applications, focusing on real-time support on the machine by web services. In the present study, standards of the OGC were used to transfer and analyze the data. For example, a weed application was mentioned in Kraatz *et al.* (2015) that is supported by the work of sensors, sending local and regional data to an "online precision farming system" which analyzed the data and refreshes the machine-located application map. Mortensen *et al.* (2019) presented a toolbox detecting regions of interest in unmanned aerial vehicles (UAV)-images by a MATLAB-toolbox. He mentioned limitations of developed image-processing by the license of the software. UAVs have become popular in agriculture, as they make fast data sampling possible. They are relative cheap platforms with a wide spectrum of possible sensors and a high resolution. Their relevance has increased in agriculture for several years. Since the platforms have reached a high level of quality, research on the sensors and their data processing has to follow (Tsouros, 2019). As PA needs a close to sense operation, scanning flights with immediate processing is an interesting possibility for field operations. Regarding this need, Geipel *et al.* (2015) used a standardized infrastructure to stream data from a UAV to a server for further analysis. Therefore, the location of the infrastructure's components does not matter, as long as interfaces are defined, and a way of transfer is given. Nowadays the location independence computing is closely linked to cloud computing.

OGC-services are prepared for the implementation into cloud computing architecture. Evangelidis *et al.* (2014) described a framework for geospatial cloud computing as a multi-tier client-server architecture, using service interfaces of the OGC. He further emphasized the benefit of the integration of computer systems into incompatible platforms by standardized interfaces. Such incompatible platforms also exist in PA. Standardized interfaces could help to overcome limitations. Exemplarily Lee & Kim (2018) realized an implementation of an OGC WPS for a geo-based image analysis in a cloud platform. He used the Platform-as-a-Service (PaaS)-technology as a scalable backend. He wanted to make the underling procedures, in the current case image processing, as modular and expandable as possible. While PaaS offers a prepared platform for the developer, it reduces efforts for setting up the infrastructure. No operating system or software has to configure on a server. The developer gets access to a working environment. A higher degree of provisioning is Function-as-a-Service (FaaS) (Van Eyk *et al.*, 2017), where the runtime environment of a function is also prepared next to the platform and could be requested by web-technologies. The benefit of FaaS is the noneffort (Van Eyk *et al.*, 2017). Sugob (2019) described FaaS as the environment on which engineers can deploy their functions or snippets of business logic.

In the current article, we explored the possibilities and capabilities of a standardized service, offering functionalities to PA-applications. We built this service, which is located directly above raw data, and supports software of the end-user via specific processing. We explored and investigated the optimal infrastructure for the realization of PA-software. Our task is to get familiar with working methods and material, like the OGC WPS and UML modelling, to analyze the activities of two PA-use-cases by UML and proof the proposed concept by realizing one use-case in real field conditions.

Material and methods

Standardization

In the present research, we focused on the potential of standards and cloud technologies for PA operations. This intention was achieved by offering service-based functions for data processing. As PA deals with location specific information, the standards of the OGC were used. Regarding the needs of PA and taking the demand of a SOA and standardization into account, attention in the development of an optimized infrastructure has to focus on the realization and publication of functions by standardized services. The OGC WPS fits best with these demands. Therefore, we analyzed its functionalities to offer descriptions and processes by a web interface.

These web services can perform anything from simple requests to complex quantitative models or analysis by artificial intelligence. The complexity is outsourced to a server offering the service. In the realized examples, a client with little computing power can calculate a vegetation index and an image analysis.

Theory from information science

In information science, the DIKW-model, representing the connectivity of data–information–knowledge–wisdom, is a theoretical framework. It describes the process of appreciation of data, while ordering terms by quality and quantity. Lokers *et al.* (2016) interpreted those processes for the agricultural domain, treating data as raw material, which is unprocessed input from sensors. Through interpretation (*i.e.*, adding meaning) the level of information is reached. This transformation could happen with models and data analysis. The level of knowledge is reached by using applications, which add options or scenarios. This level might be defined as a Decision Support System (DSS). Above all, this is the level of knowledge, reflecting interests and references. Fig. 1 expands the transformation of Lokers *et al.* (2016), who worked on the use of big data in agro-environmental science, by equivalent objects in PA. While data in PA is sampled by sensors or is delivered from databases, the step to knowledge (*e.g.* FMIS) and wisdom (field operation) crosses the information layer. Transmitted to the language of software-engineers, we expect a backend layer in preparing the data, becoming the coded functions. Currently these codes are mixed with the software of the knowledge level. A clear partition requires a separation of information and knowledge. This layer of knowledge can be described as an interface to human and machinery users. It is the visible screen design of a FMIS-client, as well as the interface to the task controller of the machine.

The separation into layers brings the benefit of a clear division of tasks. Thereby flexibility of the software increases, as layers can be treated as exchangeable elements and the development could be focused on its specific challenges. This is important, when a special expertise, as needed, for example, to analyze or model complex systems of plants in the field, is transferred to software code.

Modelling PA-operations and their proof of concept

Models are general and flexible tools, which are extensible and could be combined with others. Software developers use them to support the optimization of processes. The common construction by model-driven architecture is done by using the Unified Modelling Language (UML) to visualize and analyze context. The UML offers several modelling methods to prepare creation of software solutions after analyzing real-world processes (The Object Management Group, 2017). In particular for complex systems, dealing with several users and dependencies, the UML is a tool of choice. Papajorgji *et al.* (2009) showed the successful transfer of modelling methods from software development for developing agriculture. Nash *et al.* (2009) presented a soil testing case for a PA use.

The concept of the web-based data processing was created by a use-case based approach. Inspired by the methology of Nash *et al.* (2009) and Papajorgji *et al.* (2009) typical workflows were modeled. We developed models to fill the identified gap exemplary for two use-cases. The first complement is a scientific experiment in weed science, and it calculates a vegetation index. Second is an approach for the rescue of wildlife in pre-harvesting.

Scenario of use-case I

The modeled use-case of a weed application is based on the idea of Geipel *et al.* (2015), to connect an UAV with a field computer by a real-time communication. The developed web service enables direct analysis. In combination, this builds up the backend for field operations base on the input of an UAV above the working field. The use-case is the generation of an application map for weed management done by a tractor, which sends its position with a shift depending on speed and calculation time to the field computer. The computer requests the service to calculate a plant index by available images from the UAV. Depending on the returning value, the machine regulates its work. The calculation done by a field computer is an ambitious task. It is well suited for the export of logic to a service as a function of the service (FaaS).

Scenario of use-case II

By the scenario of a wildlife detection and deer alert system, we wish to demonstrate how the public domain could benefit from offering FaaS to farmers. Instead of functionality, the public sector already offers open data

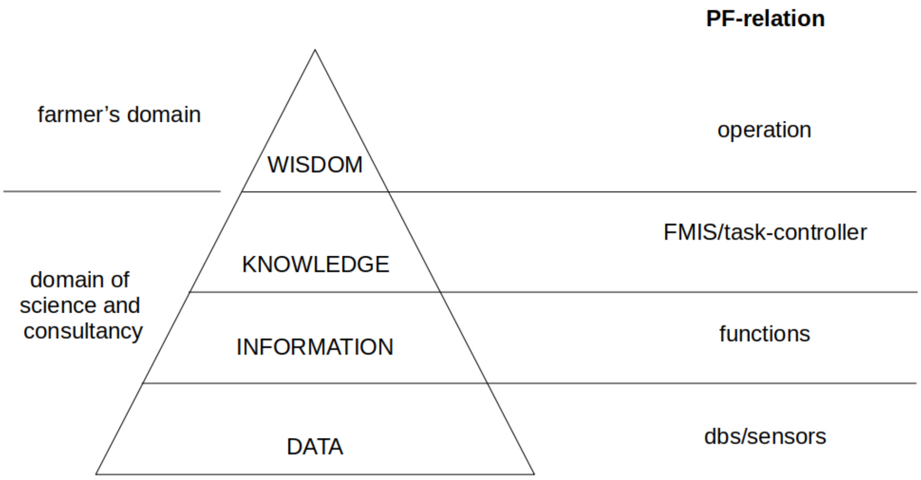

Figure1. DIKW-model adapted from Lokers *et al.* (2016) transferred to precision farming

(*e.g.* the European INSPIRE directive), and benefits are well discussed (*e.g.* Kucera & Chlapek, 2014).

Accidents involving animals during field operations are negative for the farmer as well for the public, which is interested in protection of nature. A wildlife-detection-service, financed or offered from the publicly domain, is here modelled in UML. It presents the cooperation between public authority and agriculture. The service includes the function for analysing UAV-images.

Using a model driven approach, we analyzed the needs of architecture and proofed functionality of the developed solution. The development is created towards the demands of a comprehensive, but extensible, model of activities. Thereby it focuses on business logic instead of individual details of a high-specialized sensor system. We explain which activities are expected from different chair holders, as data supplier (*e.g.* farmer), consultant/scientist/public domain, machine/farmer in an UML-activity-diagram.

We constituted a model procedure to proof the approach. From image analysis of a drone-based sampling, a vegetation index is calculated and forwarded to an application map.

Data sampling

The data sampling took place at the Heidfeld Hof research station (48.71° N, 9.18° E) of the University of Hohenheim (Stuttgart, Germany) in 2019. The average annual temperature and precipitation were 8.5 °C and 685 mm. The soil was a Luvisol derived from loess.

In 27 plots of 3 m × 23 m, winter wheat was seeded in October 2018. The row distance was 0.15 m. Eight different field treatments were performed, along with an untreated control (Table 1). In the treated plots, different weed control strategies were applied, like herbicide application, harrowing, hoeing and their combinations.

The UAV-based field surveillance was performed using a quad-copter type Phantom-4-Advanced V2.0 (Da-Jiang Innovations Science and Technology Co., Ltd, Shenzhen, China) in March 2019. The copter integrated a gimbal aligned RGB-camera with a focal length of 8.8 mm, an image resolution of 5472 × 3078 pixels and a mechanical shutter. The flight altitude was set to 36 m above ground level, resulting in a ground sampling distance of 0.99 cm.

Table 1. Treatments applied to the plots.

No. variant	Treatment
1	untreated (control)
2	herbicide
3	harrow (2x)
4	hoe (3 km/h) (2x)
5	hoe (8 km/h) (2x)
6	hoe (6 km/h) (2x)
7	harrow (1x) + hoe (1x)
8	hoe + herbicide (early)
9	hoe + herbicide (late)

Infrastructure

Geipel (2015) developed the idea of real-time information transport. The UAV is “chatting” during flight with the ground computer by predefined IT-interfaces. Data are available in real-time for further processing. We extended the described data sampling and add analysis.

The image interpretation took place in the 52° North (52°North Spatial Information Research GmbH, https://52north.org/) WPS web client (Fig. 2). The web client is a user interface, offering a map viewer and an WPS-interface. Through this interface, functions could integrate and execute from the working environment. Therefore, the service was registered to the client by naming the URL and process.

In the background an OGC WPS from a web service publishing GeoServer (Open Source Geospatial Foundation, 2020; http://geoserver.org/) was processing requests. The GeoServer is a web-based Geographic Information System (GIS), which can publish spatial data services. It ran on a Tomcat 8 (The Apache Tomcat Foundation, 2020; http://tomcat.apache.org/) server-environment. This enabled the server to act as a web server to communicate with clients, such as external software websites or, more specifically, the previously named WPS client.

The service extended the software for doing analysis for precision farming tasks. The client was not previously optimized for the operation which was added to the service by specifying the server. By choosing the specific processing from a menu, a short description appears to introduce the user to the possibilities. This additional process enriched the client-software.

Image interpretation

Image interpretation was done by the excess green minus excess red index (ExGR). ExGR has been proven for similar operations (Mink *et al.*, 2018; Gerhards *et al.*, 2020). One of the index’s main advantages was its use of “simple” color channels, as they are offered by standard RGB-cameras, which made investment costs much lower, along with the need for specialized solutions. ExGR provides quite robust results in various scenarios, by just using a zero (0) threshold. The ExGR is using the bands of an RGB-camera to calculate an index, which gives information about the vitally level of a plant and about the coverage of the ground.

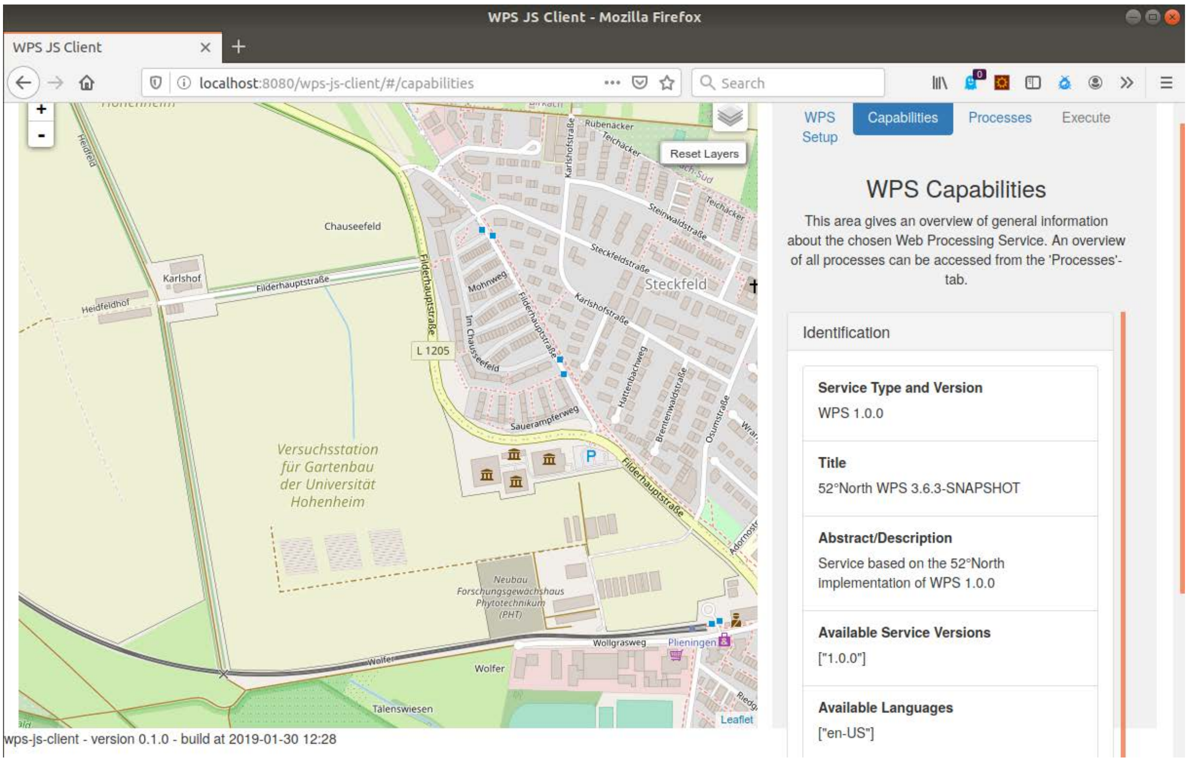

Figure 2. 52° North web client integrating the ExGR-web-service. The OpenStreetMap Viewer gives an overview complemented by an overlaying layer of the field trial's boundaries. The capabilities describe the loaded processing service.

The index uses following notation with two color indices:

$$\text{ExGR} = \text{ExG–ExR} \qquad (1)$$

where ExG (Woebbecke*et al.*, 1995) is

$$\text{ExG} = 2*g–r–b \qquad (2)$$

and ExR (Meyer *et al.*, 2004) is

$$\text{ExR} = 1.4*r–g \qquad (3)$$

Based on (2) and (3), (1) can be represented as:

$$\text{ExGR} = (2*g–r–b)–(1.4*r–g) \qquad (4)$$

where, for each pixel, g represents the value of the normalized green pixel, r represents the value of the normalized red pixel and b the value of the normalized blue pixel.

The result of the ExGR is positive for vegetation and respectively for vital vegetation. Non-vegetation objects like soil mainly cause values below zero. Our attention is on the transferability of the method. Since this calculation provided good results in the past (Mink *et al.*, 2018), our main focus is to examine how easily can it be transferred and what is its potential in a FaaS-oriented intergration.

Image processing and integration into infrastructure

Processing of the ExGR-index per plot was realized by an R-script, running on the server, which also hosted the frontend-tools. R is popular in science as a language for statistics (Team R Core, 2021). With the use of the 52 North WPS4R-extension of the OGC WPS, it was possible to offer standardized WPS-services, including the logic of R-scripts (Hinz, 2013). This was done by adding predefined comments to the script and registering it at the WPS4R-server. The preparation of R-scripts consisted of the following elements in the header:

 # wps.des: ExGR, title = Excess Green Red,
 # abstract = Calculates ExGR for raster image in chosen spatial plots.;
 # wps.in: urldir, string, abstract = "URL or directory of the data.", value ="https://www.mydatacloud.com/data";
 # wps.in: plotno, double, value=448;

In this way, the service got its name and title. The abstract was used with the client to describe in more detail what the service was about. By following the "wps.in" parameter the input to the service was defined. Beside the names of parameters that could be used in the ongoing script, there was the option of additional information and default values. In the script the lines of R-modelling of the ExGR follow. In these lines, data from the path-variable 'urldir' were imported, pointed to the directory of the image and a spatial data file, describing the polygon of each plot. A plot was chosen by the input of 'plotno' and the ExGR was calculated. The result was written directly to a file. Alternatively, it could also be written to a screen output with a line for the output:

> *# wps.out: result, string, title= values for application of selected plot;*

Results

Use-case I: Weed application

Activity-diagram

To analyze the use-case and carve out the role of FaaS, Fig. 3a presents an activity diagram of the process. It divides the activities into three instances: data supplier, which might be the same person as the farmer, machine, possibly operated by the farmer, and FaaS, which might be a consultant, a scientist or from the public domain. The central aspect is the division into the close-to-famer-operation (data-supplier and machine) and the external-operation. Second, it includes the process of data to information and knowledge. A higher knowledge about measurements in field operations is needed for an environmental situation, which is contributed by experts.

Architecture

Fig. 4 shows the basic elements of the architecture combing the field operation with a cloud service. We chose an architecture, which setup was open for a cloud environment. This environment, called the backend, was doing data processing and could be separated into a data- and a function-backend. It also offered a function for image interpretation as a service through a standardized interface. The service was used by network-access, sending requests including the specific parameters of the actual situation of operation. It was suitable for the objective to integrate innovations and knowledge into the environment with an importable function. The function was offered as a service; therefore, we used the term of FaaS.

Processing

The used R-script delivered serious results, which were identical to a local analysis, as the working script in the background was identical, as well. As expected with the different treatments, the results of each plot differed. Table 2 and Fig. 5 present the results of the ExGR. As the images are from March, plants were in the beginning of their growth period. The crop should not have achieved the majority of its canopy closure and plant coverage was expected to be below the visible soil. Negative values, as expected, represent the dominating non-vegetation areas. Even so, there are noticeable differences between the untreated (highest mean) and treated plots (*e.g.* weeder treated plots).

Use-case II: Wildlife detection

The use-case, presented in Fig. 3b, assumes that the farmer registers the field of operation at the beginning of the working day. The supporting consultant, public authority or

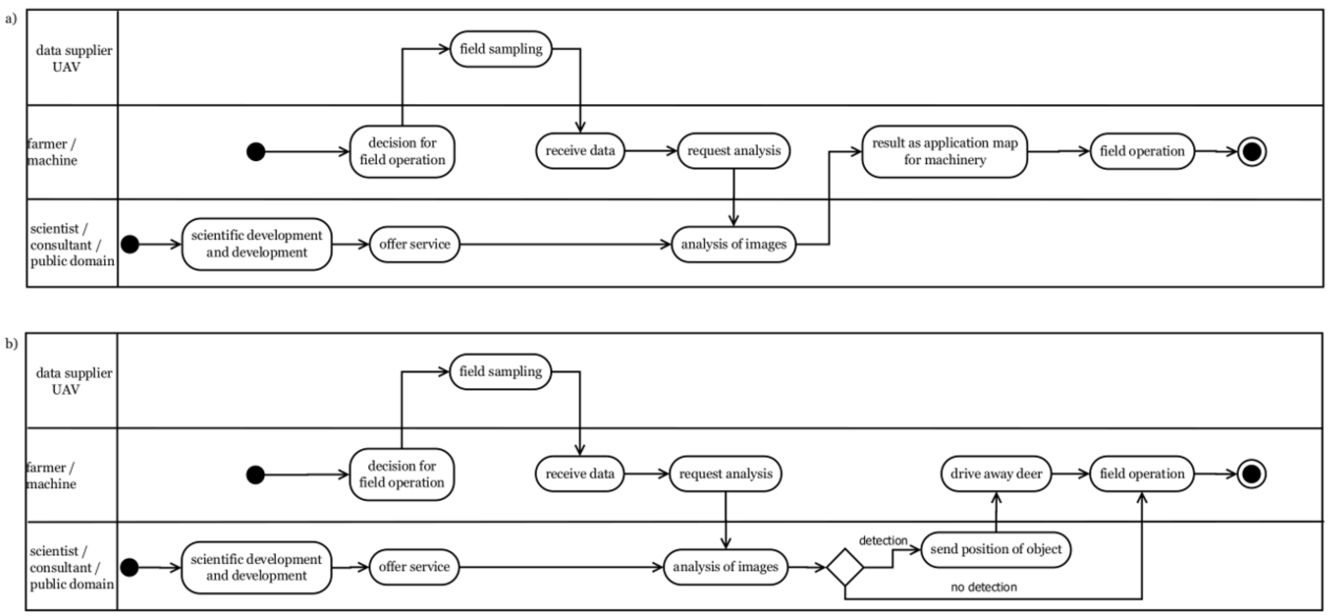

Figure 3. Activity-diagrams modelling the generation of an application map (a) and a deer alert system (b)

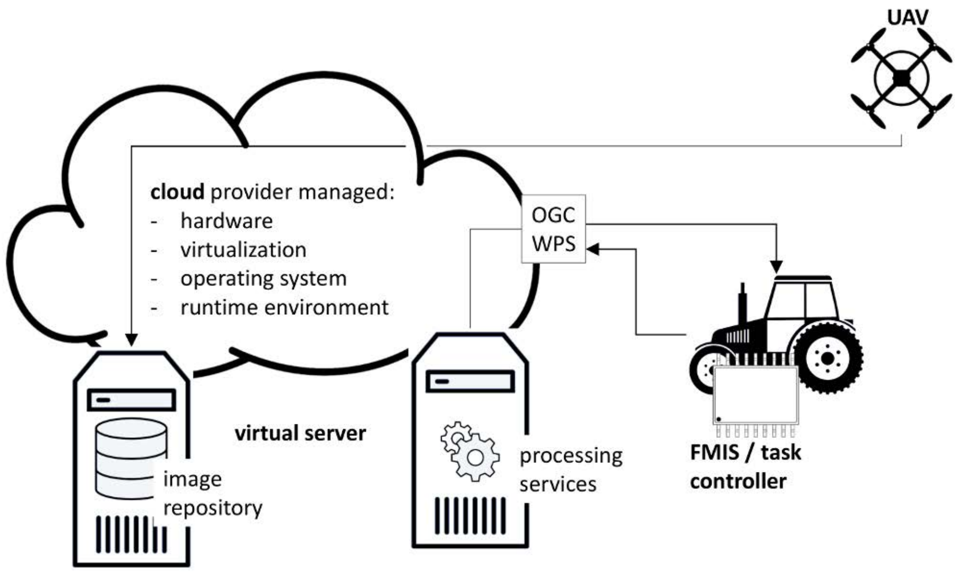

Figure 4. Schematic view of the IT-infrastructure for a drone-supported precision agriculture (PA) application. OGC: Open Geospatial Consortium. WPS: Web Processing Service.

Table 2. Results of ExGR (mean of pixels per plot) by different weed managements including their mean and standard deviation per variant

No. variant	Treatment	ExGR	Mean	Standard deviation
1	Control (untreated)	-0.183	-0.193	0.011
		-0.190		
		-0.208		
2	Herbicide	-0.183	-0.224	0.034
		-0.223		
		-0.266		
3	Weeder (2x)	-0.215	-0.242	0.024
		-0.236		
		-0.274		
4	Harrow, slow (3 km/h) (2x)	-0.199	-0.218	0.014
		-0.224		
		-0.233		
5	Harrow, fast (8 km/h) (2x)	-0.211	-0.222	0.015
		-0.213		
		-0.243		
6	Harrow, medium (6 km/h) (2x)	-0.211	-0.231	0.019
		-0.224		
		-0.257		
7	Weeder (1x) + Harrow (1x)	-0.257	-0.237	0.014
		-0.226		
		-0.228		
8	Harrow, slow (3 km/h) + Herbicide (early)	-0.191	-0.203	0.011
		-0.200		
		-0.218		
9	Harrow, slow (3 km/h) + Herbicide (late)	-0.192	-0.218	0.023
		-0.214		
		-0.248		

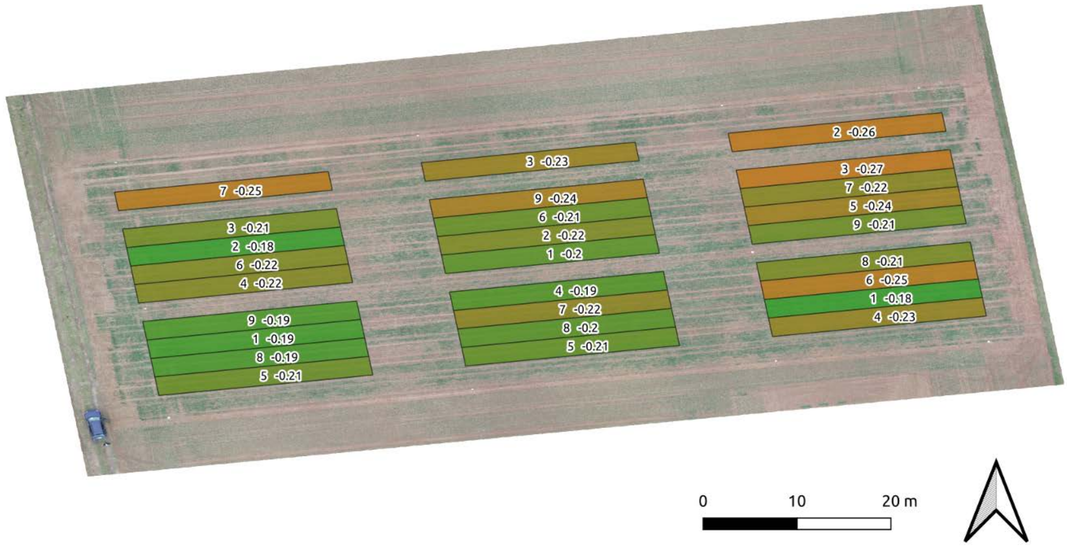

Figure 5. Map of results of different treatments and ExGR (excess green minus excess red index).

scientific institution requests data from an UAV, which are sampled on demand. With the streamed field data, a function checks for wildlife within the field. In case of a risk, it informs the machine before reaching the field-location.

The role of the FaaS is to offer a function, which is sensible enough, and its underlying infrastructure is strong enough to analyze the images with a minimum of delay. For the public authority, additional investments are needed, but there is repayment in the way of nature protection and support of local farming.

General note

Both use-cases assume a shared and common interest in the optimized operation. The results are transferable, as we noticed more or less the same components and an identical infrastructure. Even when the operation differs, the differences in the solution consists only of the algorithms for processing.

The acting group consists of a data supplier, which might be included in the person of the farmer or farming company, the machinery, which is the vendor, on the one hand, and the farmer, on the other, and consultants or public authorities, which have to improve operations by their specialized knowledge. The group of users are identical, as is the same for several parts of the modelled activities and used technologies. For example, both activities work with an UAV equipped by an RGB-camera.

Discussion

The present research works out the benefit of a decentral logic behind machinery and user interface of the FMIS. The runtime environment is server-based, flexible concerning the location of the components and open for cloud-based infrastructure. By the modelled use-cases, we present the fitness of components and their benefit for the involved parties. While Martínez *et al.* (2016) and Kaivosoja *et al.* (2013) implemented different data sources into a PA infrastructure, we added the component of processing and reached a higher level of data handling. Thereby we followed the idea of Nash *et al.* (2009) and used the WPS-standard of the OGC and implemented it as an FaaS. The benefits of an WPS as an FaaS are drawn up: we developed an infrastructure, that allows the addition of new functionalities to a user-software only by implementation of the OGC-WPS-interface. Thus, collaboration between different parties could be promoted and specific expertise could be used. Additionally, externalization of calculations onto server infrastructures is a benefit for challenging, computationally intensive operations, especially if use differs over time.

These benefits by external services are well known in other domains. We show how to integrate these techniques into agricultural field operations. Collaborative approaches between public, private and business are possible, supported by WPS- and FaaS-technologies. Software development benefits from parted functionalities. While features of software increase, time of development decreases. The process of development and updating could happen while running businesses in the background, unrecognized by the user.

The whole software is scalable by its depth of integration and calculation power. The possible increase of calculation power, in particular, supports complex algorithms. Regarding the needs of calculations in agriculture, which are used periodically and not for a whole year, FaaS could shrink available computing power and increase it on demand during field operations.

Compared to commonly known processes of data analysis, an important advantage is the processing option. While data transfer might be a disadvantage, depending on the local infrastructure. On the one hand, new mobile data transmission approaches and mobile networks are being established, and, on the other hand, technical solutions like "Moving Code" (Müller *et al.*, 2010) offer solutions. In this specific solution, code could be imported on the side of the client instead of transferring huge, sensed datasets to the server. As it uses the OGC-WPS-interface a client can use both solutions in a hybrid way. For the farmer, it is not relevant how the backend works, as long as the software functions properly, which is achieved through coordinated, standardized interfaces.

The WPS, which has been used here, belongs to a broad toolbox of standards for spatial data handling. It has been proven as a powerful instrument in manifold domains. For the transfer to PA the final result from all data processing has to reach the machinery. This was proven by Kaivosoja *et al.* (2013), Kraatz *et al.* (2015) and others in transferring operation-relevant information onto the task controller. For further developments the APIs of the OGC might be of interest, which follow actual technical developments. The present case of this work might benefit from the OGC API–processes specification (Open Geospatial Consortium, 2021).

The analyzed technologies enable an advantageous accounting model for the provider of FaaS in agriculture with the possibility of usage-oriented billing. As a result of upcoming trends in agriculture, like autonomous machines, sensor networks and sensor platforms (*e.g.*, low altitude platforms), meaning derived from actual software-architectural models increases. These models are reasonable for making the step from agro-industry to data-driven production. Thereby, decision making about the characteristics at a specific working location could be taken into account. Algorithms have to fit to local circumstances to improve PA (Dyer, 2016). The presented technologies are appropriate tools to bring this benefit to the farmer.

The same technologies and same users are involved in both use-cases. The integration of FaaS into a farming spatial data infrastructure does not need new or different UAVs and sensors. Present tools can be reutilized and extended by incorporating necessary functions for each instance of task-external knowledge. The option of using a common R-script, which is a popular method to analyze data in science, is easy to implement into PA data infrastructure. Manufacturers of a FMIS benefit by extending their offered solutions in integrating only one interface. The manufacturer gets a unique selling point through its permanent growing functions. This business model could be transferred from other markets like IT (*e.g.* open APIs of google) or the car industry (*e.g.* Mercedes-Benz/developers), where the leading brands cooperate with (other) software developers to improve their product, which do not has to be an IT-product. The idea of open interfaces supports manufacturer's efforts to open their software environments for data exchange, like Wolfert *et al.* (2017) described.

The data exchange makes a sensitive data handling necessary. For example, the General Data Protection Regulation (GDPR) of the European Union has high demands on the provider of services regarding the handling of personalized data. Its relevance increases when the systems get more open and exchange data. In our examples, accuracy per centimeter can be assigned to a landowner, a manager or a worker. This should be taken into consideration and specific protection measures and generalization techniques need to be established. One technological approach is the industrial data space. It creates spaces of different states of openness in the frame of produced datasets. The owner of a dataset keeps control of it, even if it is used by other parties. The effort of managing access rights might be too large for a single farmer, and he might then choose the simplest and safest for him way of blocking any kind of data exchange. Yet this could have negative results - both for him and for society. Here a further idea from other domains might enrich agriculture's IT-infrastructure: data cooperatives, groups with the same interests face this challenge through joint decision or the delegation to experts (Blasimme *et al.*, 2018).

The presented infrastructure offers advantages for PA with its flexibility and scalability. Every group of users gains benefit from it. First of all, the farmer gets access to a highly individualized software with adapted functions. These functions could be offered by the manufacturer itself but could also be offered by others, such as science or public authorities. An FMIS, extended by the OGC-WPS-interface, becomes a tool for the interaction of different parties. The product's quality increases, which is positive for the manufacturer. Public authorities could offer their own logic, taking regional circumstances into account, and scientists would have a way to transfer their results immediately into practice.

After the evolution towards SOAs in agriculture, FaaS-technology with collaborative partnerships might be the next step. Combined with a modular FMIS and further importing of values from external sources, or from machinery in real-time, a new way of data handling could be realized. The final improvement to field- and situational-characteristics might be the import of functions to enrich the agricultural value chain. Concrete examples of approaches could be image analysis, as depicted, but could also be error corrections of datasets, as these are calculation-intensive and appear only periodically.

The presented expansion is a main element of an agricultural IT-infrastructure, which would allow for analysis of bigger and more complex data sources. Thereby its relevance grows with the growing importance of IoT. Even mobile solutions are supported or at first enabled by the outsourcing of computational processes.

As a next step, a professional FMIS should open up for the OGC WPS interface to analyze options of integration into the user interface. In particular, description of offered functions is relevant for developer and user, depending on depth of integration. Here use of metadata, as it is usual for data analysis, is a challenge that has to be solved. Parallel to the integration of open interfaces into FMIS, products might create an ecosystem for entrepreneurship to create new solutions and improvements of PA.

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