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Integrated technical approach for differentiated nitrogen application based on expert knowledge and multiple parameters

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Integrated technical approach for differentiated nitrogen application based on expert knowledge and multiple parameters

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Am Ende hängen wir doch ab
Von Kreaturen die wir machten.

Upon the creatures we have made
We are, ourselves, at last, dependent.

Johann Wolfgang von Goethe, Faust - Der Tragödie Zweiter Teil

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CHAPTER 1

Introduction

1.1 Problem definition and complexity of site-specific nitrogen management

Mineral nitrogen (N) fertilization is a key factor for yield formation in conventional crop farming (Quemada et al., 2020) and as such, it has significantly contributed to the Green Revolution and its accompanying benefits. At the same time, it is associated with significant emissions of greenhouse gases (Balafoutis et al., 2017), as well as reactive N compounds to the environment with adverse effects on natural ecosystems and human health (Liu et al., 2022). One of the main reasons for this are ever low recovery rates even in industrialised regions due to inappropriate N management and a mismatch of N supply to the crops' spatially variable demand (Godinot et al., 2016; Mittermayer et al., 2021). Recent dramatic increases in N fertilizer prices due to natural, but also geopolitical factors are a threat to food security in many regions of the world (Schmidhuber, 2022) and further stress the need to achieve higher N efficiencies.

Variable rate N application (VRNA) based on prevailing heterogeneities within a field could prove its potential for N efficiency gains, as well as environmental and economic benefits in various research (Gobbo et al., 2021; Koch et al., 2004; Basso et al., 2016). Even though many VRNA systems have reached a commercial state decades ago, this technology is still not convincing in terms of its overall advantageousness (Lowenberg-Deboer and Erickson, 2019). The main reason for that is the enormous complexity of crop production systems having severe implications on site-specific N management and making it still a challenging task to accomplish. This can be broken down into the following core issues:

- Site-specific N management is by nature multi-parametric because it needs to consider the interactions between various biological, soil-borne, topographic and further management factors affecting crop growth (Colaço and Bramley, 2018; Corwin and Lesch, 2005).

- It is multi-dimensional because beyond spatial heterogeneities of single parameters, especially the seasonal and local influence of weather is causing temporal dynamics (Zillmann et al., 2006) that, in turn, affect the magnitude and distribution of spatial variabilities of crops and final yield (Stamatiadis et al., 2018; Taylor et al., 2003; Griepentrog et al., 2007).
- It is multi-objective because crop production can follow economic, environmental protection and productional optimization targets or a combination of these (Jones and Barnes, 2000; Ebertseder et al., 2005; Heijting et al., 2011).

In front of this background, there is an obvious need to look at it from a holistic perspective considering both, agronomic and more technical aspects.

For VRNA to respond to in-field spatial variability, the development of robust agronomic algorithms is crucial (Shanahan et al., 2008). It is obvious that beyond the crop's current N status, which can be reliably assessed with non-contact sensor technology even in real-time (Erdle et al., 2011), further relevant parameters should be considered (Auernhammer, 2001). Abundant redistribution procedures as applied by Welsh et al. (2003) and Guerrero et al. (2021) can be enhanced by the apparent electrical conductivity (ECa) as an established indicator for soil-borne productivity potential (Berntsen et al., 2006). Beyond that, algorithms based on N response models (Holland and Schepers, 2010) or crop N uptake and yield expectation are existing (Van Loon et al., 2018; Weckesser et al., 2021). Still, such algorithms are often rather rigid and partly assume models for relationships in crop physiology that can hardly be generalized (Arnall et al., 2013; Girma et al., 2007).

A fusion of various measurable, biotic and abiotic parameters is explicitly done by applying clustering techniques to define management zones of similar productivity potential, which often peculates, however, information on causal relationships (Li et al., 2007; Guerrero et al., 2021; Heege, 2013). This problem also arises in the popular use of historical yield maps, as they only represent a retrospective view and can fail in representing the patterns within a specific season (Adamchuk et al., 2011). In a more implicit manner, multiple parameters are considered together with seasonal weather influences in crop models (Gobbo et al., 2021). However, limitations concerning accuracy until midseason, the transferability among different regions and the capability of addressing spatiotemporal dynamics of N management, are preventing their broad use (Van Evert et al., 2021; Basso and Liu, 2019). Recent research intends to better consider the spatiotemporal variability in management zone delineation (Scudiero et al., 2018) and applies machine learning to respond to the inherent complexity of N management (Van Klompenburg et al., 2020). Still, there is a strong awareness that agronomic expert knowledge remains an indispensable instance for the definition of agronomic strategies, even though its consideration so far is all in all sparse (Zhai et al., 2020; Martínez-Casasnovas et al., 2018).

From a technical perspective, the complexity of site-specific N management places demands on providing and bundling different sources of information (Ostermeier, 2013). And when it comes to e.g. crop parameters or the weather, this information needs to be up to date. Further, the fusion of multiple sources of data has to be accomplished by a control implementation of the developed agronomic algorithms, which is specifically challenging, especially when the information needs to be processed in real-time. In such cases, the interaction with application systems also comes into play, whereby the magnitude of the spatial variability of different parameters has to be considered (Han et al., 1994). This affects on the one hand the transversal direction, where pragmatic analyses focusing on field-related heterogeneities concluded that common working widths are abundantly too large (Griepentrog et al., 2007; Morari et al., 2021). On the other hand, the longitudinal direction needs to be considered as the application system successively covers the field. There, application errors can usually be traced back to the application system's response (Fulton et al., 2013; Sharipov et al., 2021) and the spatial discrepancy between sensing and application (Goense, 1999).

From an overall view of a technical system for VRNA, it can be concluded that the most crucial components need to provide interfaces for human-machine interaction because full automation is still far ahead and consequently, the user is a core control element (Zhai et al., 2020). A big challenge hereby is to take out complexity by keeping the level of interaction for the user as low as possible, while at the same time the process to be controlled remains highly complex (Ferrise et al., 2021; Tummers et al., 2019). As the entire VRNA is a distributed process mainly consisting of a management and an execution part, which can both be subdivided into further sub-processes, there are also high organizational efforts needed in linking them with each other and exchanging necessary information.

1.2 Agronomic relevance and incorporation of expert knowledge

With the advancing digitisation of crop production, further improvements in sensor technology and automated decision-making with the aid of big data and artificial intelligence can be expected. However, this should not disregard the highly important potential that agronomic expert knowledge of a majority of farmers and advisors has in defining agronomic strategies (Wolfert et al., 2017). Their professional education incorporating some kind of standard scientific knowledge, as well as their access to various kinds of information relevant to the production enables them to accommodate biological, management, economic and technical requirements (Heijting et al., 2011; Quemada et al., 2020; Oliver et al., 2012). This is leveraged by farm-specific, local and situative knowledge (Oliver et al., 2010; Lundström and Lindblom, 2018), which is accumulated over many years of experience acquired during the work on one complex production system (Hoffmann et al., 2007). Thereby, they gain a feeling for the parameter interrelations under different seasonal scenarios, as well as the peculiarities of their fields, which is already applied in the crop and field assessment prior to every split N application (Isensee et al., 2003). As a consequence, the principle of precision farming has been adopted by many farmers since the earliest days of mechanisation as they e.g. vary N dose rates (DR) manually based on their intuition (Lowenberg-Deboer and Erickson, 2019). Expert knowledge has been employed as the main element in the definition of VRNA strategies (Ferrise et al., 2021; Ostermeier et al., 2007) and attempts were made to tap it for management zones delineation and improvement (Fleming et al., 2000; Guerrero et al., 2021).

The technical integration of expert knowledge is in general a big challenge in agricultural decision support systems (DSS) (Dutta et al., 2014). A common way is using intelligent computer programs like expert systems and in this context, fuzzy systems are particularly suitable for generating robust algorithms and interpreting large amounts of spatial data (Tagarakis et al., 2014). Their popularity in the area of complex, multi-parametric and non-linear control problems can be attributed to the fact that they allow a straightforward system setup without complex mathematical models (López et al., 2008). The underlying theory of fuzzy logic, which goes back to Zadeh (1965), is rather mimicking human reasoning (Zadeh, 1983). It is working with membership functions to define fuzzy classes of parameter values, as well as linguistic terms and rules, which define the fuzzy system's basic behavior. Therefore, it inherently considers the fact that human knowledge is affected by significant blurredness, subjectivity and uncertainty, which is also true for many natural phenomena (Guillaume et al., 2012; Ashraf et al., 2014). Fuzzy systems enable also high flexibility in adjusting the control strategy to varying circumstances (Van der Werf and Zimmer, 1998), which is crucial for agricultural DSS (Rose et al., 2016). Because of all these factors, they found numerous applications in multi-parametric control of agricultural processes (Assimakopoulos et al., 2003; Lavanya et al., 2018; Rueda-Ayala et al., 2013) and particularly site-specific N management (Bouroubi et al., 2011; Tremblay et al., 2012). Leroux et al. (2018) presented an approach to explicitly rely on expert knowledge for a fusion of multiple mapped parameters with the aid of a fuzzy system. However, a systematic approach for a user-centered and situative N management is still pending and requires optimizations along the entire process chain of VRNA.

1.3 Technical perspective on optimized variable rate nitrogen application

If one wants to address the entire VRNA process chain with an integrated technical approach, the agronomic algorithms have to be considered as the core component, whereby the heterogeneous origin of multi-parametric data is an important technical aspect (Guillaume et al., 2012). In the context of VRNA, the fusion of real-time sensor data with mapped parameters can be regarded as the most challenging out of realistic constellations and should therefore be considered as a benchmark for the development of multi-parametric VRNA systems. Especially when expert knowledge is to be used to define the VRNA system behavior, its integration plays a more important role than the technical aspects of real-time fusion (Ostermeier et al., 2003). Therfore, the first focus needs to be on the methodical realization and analysis of expert knowledge integration.

Building on this, the execution of the VRNA at the field level can be regarded as the next main process step. This requires the implementation of the developed algorithms in an automatic control and its incorporation into an application system consisting of a real-time sensor, tractor and applicator, whereby for granular fertilizer, centrifugal spreaders are the most abundant ones due to their low cost, robustness and simplicity of use (Nørremark et al., 2017; Van Liedekerke et al., 2009). Ostermeier (2013) described conceptually, how a real-time data fusion based on an expert system can be implemented. To synchronize the fertilizer application with defined setpoint rates (SR), research was conducted on technical latencies within the application system (Maleki et al., 2008; Yinyan et al., 2018), as well as on the compensation of spatial offsets between DR definition and realization with temporal delays (Cai et al., 2017; Chen et al., 2018). Trajectory planning was used in robotic systems to account for this discrepancy (Cruz Ulloa et al., 2022) but for commercial application systems, a dynamic offset optimization was only formulated and examined theoretically by Griepentrog and Persson (2001).

In particular, the inclusion of the user as the central element for defining the VRNA strategy places high demands on the entire VRNA process chain. An important focus is on the system's knowledge acquisition, which finally defines its behavior and needs to be conducted close before each N application to respond to the specific situative circumstances. In front of this background, it is obvious that for such a system to be applicable, the knowledge engineer bridging the technical barrier between the user and the system needs to be replaced by employing an intelligent and powerful knowledge acquisition component that can communicate with the expert, thus heading towards direct knowledge acquisition (Ostermeier, 2013). For this, various challenges and requirements on DSSs as defined by the Software Quality Requirements and Evaluation (SQuaRE) standard (ISO/IEC

25010:2011) and further refined by Zhai et al. (2020) in terms of agricultural DSSs come into play. User interfaces are of specific importance and their design has an enormous impact on the acceptance and thus, the success of a user-centered VRNA system (Krishnan et al., 2016; Oliver et al., 2012). Currently, this is a significant bottleneck for many agricultural DSSs (Tummers et al., 2019). Further important aspects are the provision of the necessary information for the decision making, as well as feedback on its implications and options for its refinement (Weckesser et al., 2021). Especially since a strong user-centeredness in the VRNA strategy definition takes up a significant time budget during a seasonal phase of already existing work peaks, the use of digital tools is necessary to ease data management and automate data transfer among different subsystems (Lindblom et al., 2017). Since the whole VRNA process chain necessarily consists of distributed systems, a web-based design is a fundamental prerequisite for that (Bökle et al., 2022).

1.4 Aim and objectives

The aim of this work is to provide technical methods to approach the complexity of site-specific N management in terms of decision making, as well as the technical and organizational realization in a systematic manner. To fulfil this aim, the following objectives are pursued:

- Analysis of functional limitations of established VRNA systems
- Methodological basis of a real-time capable fuzzy expert system for VRNA
  - Valid imitation of an established system's algorithms in a fuzzy system
  - Extension to a multi-parametric fuzzy expert system and analysis of study cases
- Technical implementation of real-time data fusion and precise applicator control
  - Development of a real-time control with an inference engine and algorithms for spatial synchronization of DR determination and application in different sections
  - Incorporation into a real application system
  - Verification with comprehensive field tests and subsequent analyses
- Design of a consistent digitized process chain for VRNA
  - System architecture description and functional analysis
  - Prototypic implementation of core components for proof of concept

1.5 Appended papers

The dissertation is based on the following three papers:

A. Heiß, A., Paraforos, D.S., Sharipov, G.M., Griepentrog, H.W., 2021. Modeling and simulation of a multi-parametric fuzzy expert system for variable rate nitrogen application. Computers and Electronics in Agriculture 182, 106008. https://doi.org/10.1016/j.compag.2021.106008

B. Heiß, A., Paraforos, D.S., Sharipov, G.M., Griepentrog, H.W., 2022. Real-time control for multi-parametric data fusion and dynamic offset optimization in sensor-based variable rate nitrogen application. Computers and Electronics in Agriculture 196, 106893. https://doi.org/10.1016/j.compag.2022.106893

C. Heiß A., Paraforos D.S., Sharipov G.M., Ullrich, P., Bruns, J., Abecker, A., Griepentrog, H.W., 2023. Versatile and user-centered concept for temporally and spatially adapted nitrogen application based on multiple parameters. European Journal of Agronomy 145, 126792. https://doi.org/10.1016/j.eja.2023.126792

In Paper A, the methodical basis for a multi-parametric and real-time capable fuzzy expert system was described. Data were acquired under different field conditions with a marketable real-time sensor system and a fuzzy logic based model of its agronomic algorithms was identified, optimized and validated. Soil ECa data were used for the extension to a multi-parametric fuzzy expert system and the analysis of different realistic scenarios. In Paper B, a control system for real-time inference based on the fuzzy expert system, as well as an SR control compensating inherent technical latencies and spatiotemporal discrepancies between sensing and application in a differentiated manner was developed and incorporated into a sensor-tractor spreader system. Using data from a real use case, field tests with various driving speed scenarios were conducted and subsequently analyzed with regard to the control system's performance. A consistently digital and web-based VRNA process chain for agile site-specific N management based on expert knowledge and multiple parameters was conceptualized in Paper C. User interfaces and crucial components were prototypically implemented for the use case of a real-time application with preceding simulation to evaluate the potentials and limitations of the approach and specify further requirements regarding its implementation.

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CHAPTER 2

Paper A

Modeling and simulation of a multi-parametric fuzzy expert system for variable rate nitrogen application[1]

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Hans W. Griepentrog

Abstract

Nitrogen (N) excess due to mineral fertilization in conventional crop farming has a significant negative impact on the environment. Variable rate N application (VRNA) is a promising tool to increase N recovery rates in spatially heterogeneous fields. Real-time sensor systems for VRNA usually consider only the crop's N status and their fertilization algorithms are abundantly deterministic. Due to their education and professional experience, farmers have a considerable knowledge base that should be used to describe the dynamic and non-deterministic interactions of multiple parameters for a locally adapted N fertilization. Fuzzy systems present an effective way to integrate expert knowledge into an automated multi-parametric control. This paper describes, how fuzzy logic can be used to fuse the plant-related information from a real-time sensor system with further parameters to create a multi-parametric system for VRNA. Using sets of input-output data acquired with a Yara N-Sensor ALS2 system, an adaptive, fuzzy logic-based model of its agronomic algorithms was identified, optimized and validated. The results indicated high accordance with the N-Sensor algorithms and good automated adaptability to different calibrations with values of the Pearson correlation coefficient higher than 0.99 and a maximum percentage root mean square error

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of 0.14%. In a case study, the model was combined with the apparent soil electrical conductivity (ECa) as an indicator for spatially varying soil productivity, as well as a case distinction for different weather conditions. Simulations with historic ECa data and N-Sensor recordings have shown the high flexibility of the multi-parametric fuzzy expert system. With the presented method, specific deficiencies of one-parametric approaches can be moderated and the application can be adapted to the prevailing conditions in a straightforward manner. Also, the target orientation could be influenced based on the specific preferences of the expert.

Keywords: artificial intelligence, fuzzy expert systems, variable rate application, real-time sensor systems, multi-parametric data fusion

Nomenclature

CF	cutoff factor
DR_{FIS}	dose rate outputted from the FIS, kg ha^{-1}
DR_{max}	maximum dose rate, kg ha^{-1}
DR_{min}	minimum dose rate, kg ha^{-1}
DR_{YNS}	dose rate outputted from the N-Sensor system, kg ha^{-1}
ECa	apparent electrical conductivity, mS m^{-1}
ECa_{max}	maximum raster value of the interpolated ECa map, mS m^{-1}
ECa_{mean}	mean raster value of the interpolated ECa map, mS m^{-1}
ECa_{min}	minimum raster value of the interpolated ECa map, mS m^{-1}
FIS	fuzzy inference system
GS	growth stage
N	nitrogen
N2	second N application
N3	third N application
R	Pearson correlation coefficient
RMSE	root mean square error, kg ha^{-1}
$RMSE_p$	percentage root mean square error, %
RR	reference rate, kg ha^{-1}
SN	normalized sensor value, kg ha^{-1}
SN_{cut}	cutoff sensor value, kg ha^{-1}
SN_{ref}	reference sensor value, kg ha^{-1}

SL slope of the N-Sensor system's calibration curve

VRNA variable rate N application

2.1 Introduction

On a global average, only about 50% of the mineral nitrogen (N) applied on cropland via synthetic fertilizer is used by the crop itself (Lassaletta et al., 2014). Excess of reactive N to the environment can lead to pollution of air and water resources and is causing greenhouse gas emissions. In the future, the use of N fertilizer as one of the main drivers of biomass production in conventional farming can only be justified with an increase in recovery rates. Variable rate N application (VRNA) can respond to in-field heterogeneities and is considered therefore as a promising approach to increase N exploitation (Balafoutis et al., 2017; Griepentrog and Kyhn, 2000).

Beyond satellite-based or airborne approaches, real-time sensor systems for VRNA are on the market today (e.g. Claas Crop Sensor Isaria, Topcon CropSpec). They are measuring the crop's N status via the spectral response at specific wavelengths, determining the N need based on deposited algorithms and controlling the applicator in real-time. Introduced in 1999, the Yara N-Sensor is one of the earliest commercially available real-time systems. Even if several studies are indicating that the N-Sensor system could bring economic and environmental benefits, farmers still have reservations about that technology because they shy away from the presumed additional cost and work or have doubts of the benefits (Lindblom et al., 2017). The dosing algorithms implemented in real-time sensor systems are rather deterministic and they can only be adapted to a limited extent to the highly varying circumstances prevailing at each specific application. Their behavior is still subject to controversial discussions among agronomic experts. As plant growth is the result of various biotic and abiotic factors, the sole consideration of single parameters is insufficient to deduce demand-driven dose rates (Colaço and Bramley, 2018; Griepentrog et al., 2007). Map-overlay approaches for real-time sensor systems are existing (Paraforos et al., 2019). However, they usually do not represent a numeric fusion of different parameters.

Measurements of the apparent soil electrical conductivity (ECa) present an effective way to gain high-resolution patterns from the soil's spatial variability. The measurements are frequently used to indicate soil texture and particularly the clay content in non-saline soils (Heil and Schmidhalter, 2017). Anderson-Cook et al. (2002) stated that with ECa measurements via electromagnetic induction, soil zones of differing productivity potential can be delineated for use in variable rate fertilization strategies. The same authors found positive correlations between ECa and crop yield, whereas Kitchen et al. (2003) found both, positive and negative relations on different sites in the USA with distinct climatic and soil conditions. Therefore, the relationship between ECa and crop productivity is not straightforward and ECa readings must be interpreted in the context of climate and soil conditions prevailing at a specific location.

A sustainable N-fertilization must take into account the high vagueness and the dynamic interactions between the different parameters in the natural system. Knowledge-based and artificial intelligence techniques can perform better in modeling complex systems than conventional descriptive statistics, analytical methods and multiple regression (Abbaspour-Gilandeh and Abbaspour-Gilandeh, 2019; Jahangiri et al., 2019). As most of the natural phenomena are fuzzy, fuzzy systems present an effective and structural way of dealing with decisions involving the inherent uncertainties and non-linearities of environmental processes and parameters (Papadopoulos et al., 2011; Ashraf et al., 2014; Mendes et al., 2019). Fuzzy systems are based on fuzzy logic, which is much closer in spirit to human thinking and natural language than traditional logical systems and thereby provides a mean to integrate expert knowledge via linguistic terms into an automatic control strategy (Lee, 2005). They show a relatively good robustness and fault tolerance, as well as a simplified system design with multiple features of variable relation described by practical experience instead of mathematical modeling (Sun et al., 2018). Sivanandam et al. (2007) are stating that fuzzy expert systems are flexible because the membership functions for the single parameters can be changed dynamically according to the specific situation and that such an adaption can be automated by developing self-learning modules.

In recent years, the use of fuzzy systems in spatial problems is increasing (Ashraf et al., 2014). Mendes et al. (2019) presented an irrigation system based on fuzzy logic. They emphasize the attractiveness to farmers due to the simple system setup. A fuzzy system to reduce fertilizer consumption and improve crop productivity was presented by Prabakaran et al. (2018). It is considering soil, water and agronomy parameters, as well as expert knowledge. Papadopoulos, Kalivas and Hatzichristos (2011) developed a decision support system based on knowledge elicitation and fuzzy logic methodologies for site-specific N fertilization. The application of fuzzy logic to improve variable rate controller responses is presented by Liang and Wang (2010). Tremblay et al. (2010) included expert knowledge and experimental results in a fuzzy system for VRNA. As input parameters, the system used spectral crop information, as well as the ECa and topographic parameters. The work of Bouroubi et al. (2011) is based on that approach and respected ECa and precipitation together with spectral crop data. With both approaches, economically optimal N rates were estimated. Even they were both very much adapted to specific study fields, they present the first step towards a VRNA that could be adapted to varying conditions by applying expert knowledge with fuzzy logic.

Farmers have pronounced expert knowledge because they are working their whole working life on one complex farm experiment (Hoffmann et al., 2007). With a fuzzy expert system, the farmers' specific site knowledge and recognition of the plant production process could be transferred to a multi-parametric VRNA in a straightforward manner, without the need of costly experiments to define the parameter interactions. In this way, the VRNA could be adapted to the varying conditions of a specific application, as well as to different target orientations. The use of such an approach to fuse the plant-related information from real-time sensor systems with further parameters is still an open question. This paper describes in a first step, how the agronomic algorithms of the Yara N-Sensor system can be imitated with a fuzzy logic-based model in an automated way. Initial approaches to that are presented in Heiß et al. (2020). The aim is to use this as the basis for including more parameters towards developing a multi-parametric system. The model is extended by the soil ECa as a further input parameter, as well as a case distinction for different weather conditions. Specific objectives of the present study are the identification and optimization of the fuzzy logic-based N-Sensor model using a recorded set of input-output data. Then, the automatically adjusting model is validated with further data sets. Finally, a case study is developed to simulate the outputs of a multi-parametric fuzzy expert system using historic ECa and N-Sensor data and assuming different weather conditions.

2.2 Materials and methods

2.2.1 Instrumentation and field measurements

In spring 2019, measurements were made using a Yara N-Sensor ALS-2 system operated with the N-Sensor 4.5 software (Yara GmbH & Co. KG, Dülmen, Germany). In the N-Sensor ALS-2, two sensor heads are mounted on a traverse, which in turn is mounted on the tractor roof. The tractor used for the measurements was equipped with an Autopilot automatic steering system (Trimble Inc., Sunnyvale, California, USA) allowing to tap position data from the integrated RTK-GNSS for georeferencing the measurements. Its antenna was also placed on the tractor roof with a distance of 0.5 m behind the N-Sensor traverse. In Figure 2.1, the system setup is shown together with a schematic illustration of the data flow for the N-application mode. Even there are several other operation modes like e.g. N-Sensor scanning or free calibration, this mode was chosen because it was recommended by the manufacturer for conduction of the measurements.

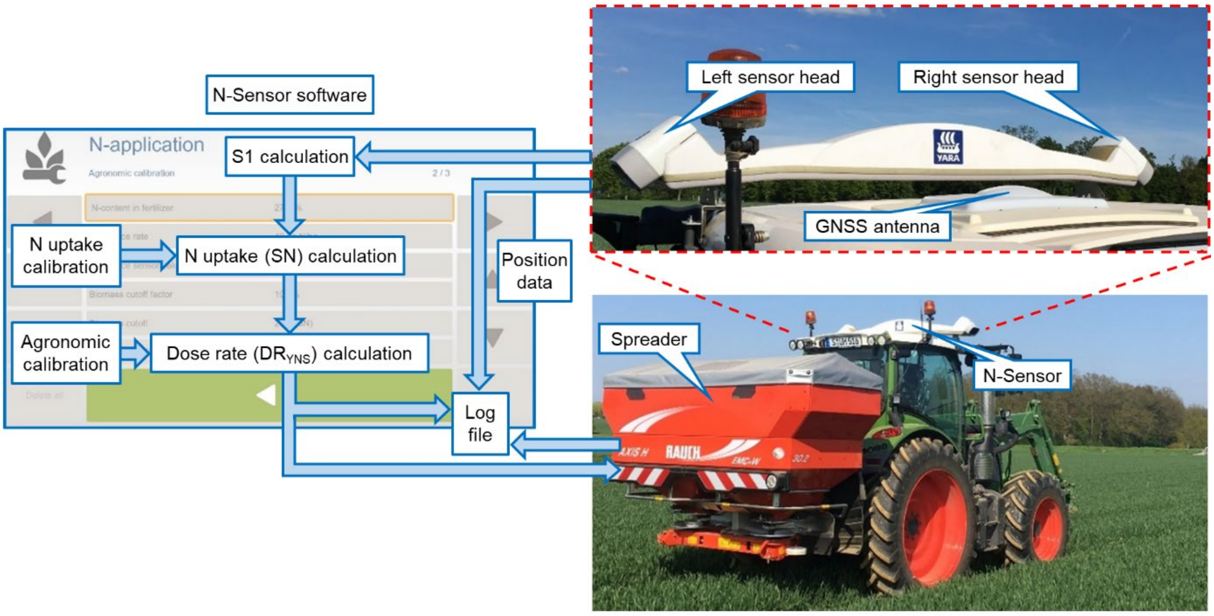

Figure 2.1. Yara N-Sensor ALS-2 system setup with schematic data flow for the N-application mode (blue arrows).

During operation in the N-Application mode, the sensor heads are emitting light flashes and measuring the crop reflectance at specific wavelengths (670, 730, 740 and 770 nm). Based on that, the S1, which is a proprietary vegetation index from Yara, is calculated at a frequency of 1 Hz. In a second step, the software calculates a normalized sensor value (SN), which corresponds to the N uptake of the crop in kg ha^{-1}. Using that indication about the crop's N status, a fertilizer dose rate (DR_{YNS}) is calculated, settled to the N content of the fertilizer and forwarded to the spreader control. From there, the actual applied rates can be sent back to the N-Sensor software. The whole process from spectral measurements to the control of the spreader is conducted in real-time during the fertilizer application. Before the application, the system needs to be calibrated. The calibration for the N uptake is done by giving the crop type and the Zadoks growth stage (GS) (Zadoks et al., 1974). For the agronomic calibration, a reference SN value (SN_{ref}) is defined and assigned to a reference rate (RR). The RR corresponds to the amount of N in kg ha^{-1}, which an agronomic expert would give to a crop having the SN_{ref}. In order to limit the application between certain thresholds, a minimum and maximum can be set for DR_{YNS} (DR_{min} and DR_{max}, respectively). Furthermore, the software is automatically setting a biomass cutoff value (SN_{cut}) within the agronomic calibration. Below that threshold, the system is strongly decreasing the DR_{YNS}. After starting a task, the system software automatically saves the calibration settings and records a range of parameters like e.g. the GNSS position, the SN and the DR_{YNS} within a log file at the measurement frequency of 1 Hz.

The measurements took place at the research farm 'Ihinger Hof' of the University of Hohenheim (48°44'41.61"N, 8°55'26.42"E). Three fields with winter wheat (*Triticum aestivum L.*) were chosen, where the N fertilization was split into three applications at different GSs, which is common practice. In Figure 2.2, the field boundaries, as well as the georeferenced points of the measurements conducted in the scope of the second application (N2) are presented. The tracks corresponded to the tramlines having a spacing of 24 m and they were followed also for measurements at the third application (N3). For the first application, there were no measurements because the variability in the wheat's N status is low at that stage and, consequently, this is not a common use case for the N-Sensor. For each application, specific RRs were defined for a whole field or subareas of a field based on a crop assessment. Reference plots were chosen within each field or subarea, respectively, to determine the SN_{ref}. They had a length of approx. 50 m and were supposed to reflect the crop development, to which the agronomic expert would assign the specific RR. During the agronomic calibration in the N-Sensor software, they were measured at a speed of approx. 2.2 m s^{-1}, which was also the speed for the subsequent measurements. The software calculated the average SN on the plot and took it as the SN_{ref}. For all measurements, DR_{min} and DR_{max} were set to 0 and 120 kg ha^{-1}, respectively.

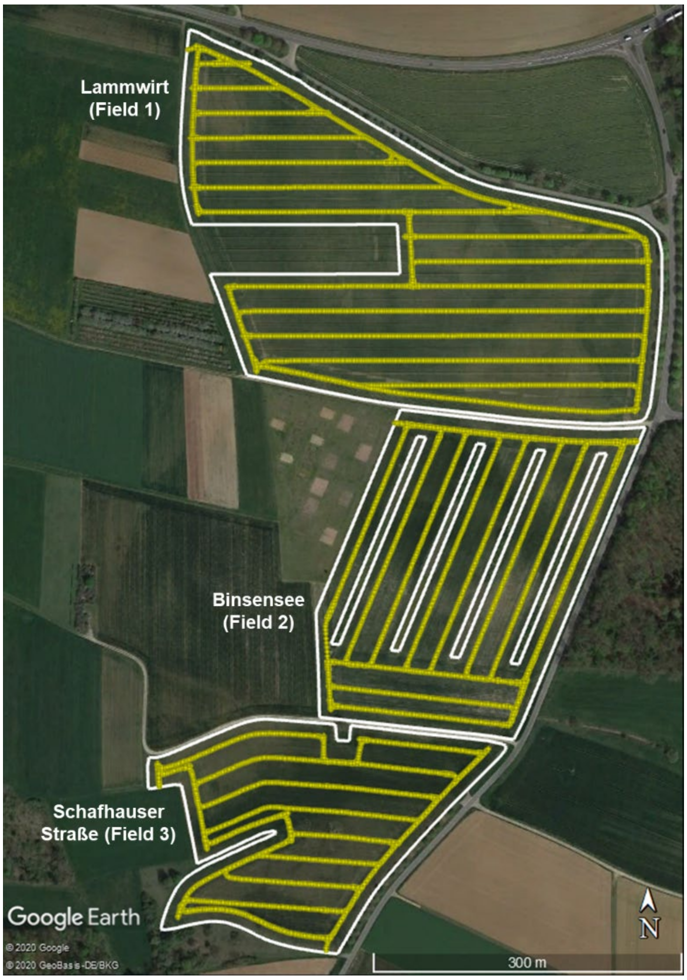

Figure 2.2. Satellite view with the field boundaries (white lines) and georeferenced measurements (yellow dots) from N2.

For N3, the yield-oriented strategy of the N-application mode was chosen, which was behaving in a similar way to the N2 strategy in terms of the derivation of DR_{YNS}. The quality-oriented strategy for N3 would have been behaving in a rather contrary way. The recorded files were converted to CSV format for further processing. In order to eliminate implausible values and avoid repetitions at the same site, measurements recorded at zero speed or located outside the field boundaries were deleted. Key data from the recorded data sets are given in Table 2.1.

Table 2.1. Key data of the measurements.

Acronym	Field/Subarea	Date	GS	SN_{ref} [kg ha^{-1}]	SN_{cut} [kg ha^{-1}]	RR [kg ha^{-1}]	Range SN [kg ha^{-1}]
N2 (Second fertilizer application)							
$N2_1$	Field 1	01 May 2019	31	54.3	20	30	21.7-75.2
$N2_2$	Field 2	25 April 2019	31	80.4	20	40	26.9-103.7
$N2_3$	Field 3	01 May 2019	31	83.5	20	40	27.7-103
N3 (Third fertilizer application)							
$N3_1$	Field 1	31 May 2019	39	122.2	54	72	45.5-144
$N3_{2NW}$	Field 2 North+West	31 May 2019	49	142.9	54	47	6.7-194.3
$N3_{2SE}$	Field 2 South+East	31 May 2019	39	135.2	54	47	85.2-157.1
$N3_{3N}$	Field 3 North	31 May 2019	39	134.7	54	87	51.9-153.2
$N3_{3S}$	Field 3 South	31 May 2019	39	118.5	54	37	104-157

2.2.2 Principles of Takagi-Sugeno fuzzy systems

For modeling of the fuzzy expert system, Takagi-Sugeno inference was chosen because of its advantages in terms of working with linear, as well as optimization and adaptive techniques

(Sivanandam et al., 2007). In Figure 2.3, the basic operating principle of a Takagi-Sugeno fuzzy inference system (FIS) with two input parameters and one output parameter is schematically illustrated. For each input parameter, fuzzy sets are defined in advance that can be described by membership functions. Linguistic terms are assigned to these fuzzy sets. Thus, for each input value within the respected range, a certain degree of membership to each fuzzy set is defined. The degree of membership can have values between zero and one. For the output parameter, linguistic terms are assigned to singletons, which is a special characteristic for Takagi-Sugeno FISs. In the rule base, the behavior of the system is determined by a definition of the interrelations between input and output parameters. This is done by connecting the corresponding linguistic terms using 'IF-THEN' conditionals. A conjunction of the input parameters can be realized with 'AND' or 'OR' operators, respectively. A weight can be assigned to rules to express their trustworthiness. Consequently, also the relative importance of different input parameters can be taken into account.

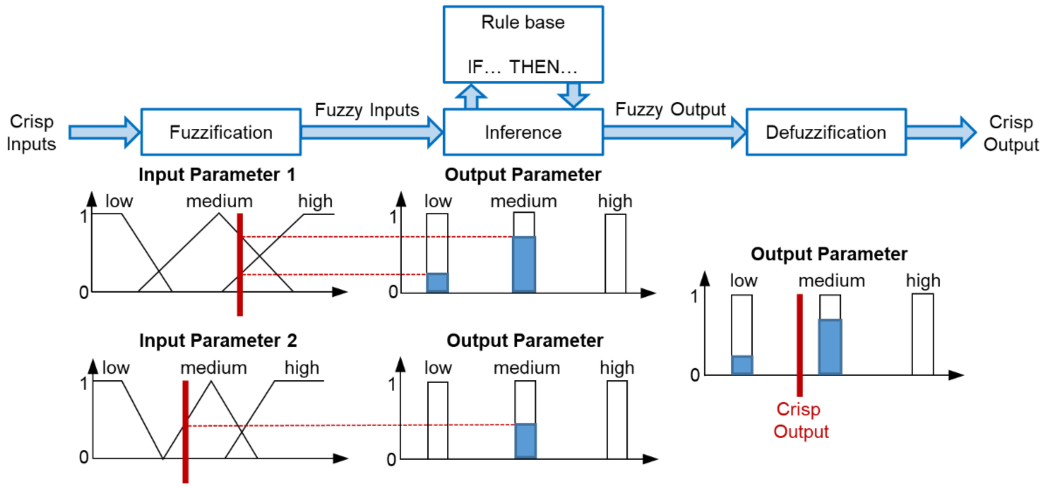

Figure 2.3. Schematic operating principle of a fuzzy system with Takagi-Sugeno inference, two input and one output parameters.

During operation, degrees of membership are determined from crisp input values in the fuzzification. Depending on which fuzzy sets are affected, the corresponding rules are fired. In the inference, methods of propositional logic are applied to realize an implication on the output, which consists of weighted singletons. The fuzzy outputs resulting from the fired rules are aggregated and defuzzified to gain a crisp output value from the results. Different methods for these steps exist, whereby for the aggregation, the max-accumulation, and for the defuzzification, the formation of a weighted average are very common (Jantzen, 2007).

2.2.3 Fuzzy logic-based N-Sensor model

2.2.3.1 Identification of the model

Using the fuzzy logic toolbox of MATLAB R2019a (The Mathworks Inc., Natick, Massachusetts, USA), a fuzzy logic-based model of the N-Sensor software's dosing algorithm was developed, which was supposed to be functional for the use case of N2 and a yield-oriented N3 in winter wheat. It is known from the technical documentation of the used N-Sensor software that the relation between SN and DR_{YNS} is piecewise linear. For the defined use case, the calculated DR_{YNS} is negatively linear to the SN for values above the SN_{cut}. The specific slope (SL) of this section depends on the agronomic calibration, whereas the y-axis intercept varies depending on the RR and SN_{ref}. This section is then virtually cut by DR_{min} and DR_{max}. Below the SN_{cut}, the DR_{YNS} is strongly reduced with decreasing SN values. As a basis of the model, Takagi-Sugeno FISs with triangular and trapezoidal input membership functions were developed to imitate the relationship between SN and DR_{YNS}. In particular, the formation of the FISs was based on the SL indicated in the log file, the SN_{ref}, the SN_{cut}, the RR, the DR_{min}, as well as the DR_{max} values originating from the agronomic calibration, to ensure the adaptability of the model to different calibrations. Beyond that, a cutoff factor (CF) was introduced to better modulate the intensity of the DR_{YNS}'s drop for SN values below the SN_{cut}. For the input parameter SN, the overall considered input range of the FISs was $[0 \;\; (1.5 \times SN_{ref})]$.

In a first step, the algorithm for the model was configured to create a FIS with two fuzzy sets with triangular membership functions (*'low', 'medium'*) and two fuzzy sets with trapezoidal ones, respectively (*'cutoff'* and *'high'*). The exact shape of the membership functions can be characterized by parameters, whereby for a triangular function, parameters a and c of $[a \;\; b \;\; c]$ define its feet, and b defines its peak. For trapezoidal functions, parameters b and c of $[a \;\; b \;\; c \;\; d]$ define the shoulders, and a and d define the feet. The parameters were set as follows:

$$Cutoff\text{: } [0 \;\; 0 \;\; (CF \times SN_{cut}) \;\; SN_{cut}]$$

$$Low\text{: } \left[(CF \times SN_{cut}) \;\; SN_{cut} \;\; SN_{ref}\right]$$

$$Medium\text{: } \left[SN_{cut} \;\; SN_{ref} \;\; \left(\frac{DR_{min} - RR + SN_{ref} \times SL}{SL}\right)\right]$$

$$High\text{: } \left[SN_{ref} \;\; \left(\frac{DR_{min} - RR + SN_{ref} \times SL}{SL}\right) \;\; \left(1.5 \times SN_{ref}\right) \;\; \left(1.5 \times SN_{ref}\right)\right]$$

In Figure 2.4, the basic setup of the input membership functions is illustrated schematically.

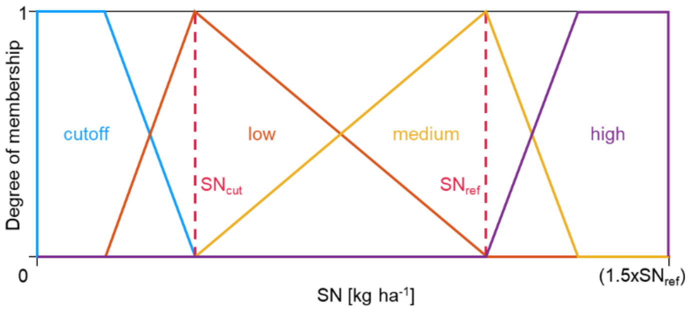

Figure 2.4. Schematic illustration of the membership function setup for the input parameter SN with *low* having a triangular shape.

For the DR outputted from the FIS (DR_{FIS}), four singletons were defined (*'cutoff'*, *'low'*, *'reference'*, and *'high'*). For *cutoff* and *low*, the value was always DR_{min}, whereas *reference* corresponded to RR. For high, the calculation was as follows:

$$High: RR - SL \times (SN_{ref} - SN_{cut})$$

The following rules were defined to imitate the behavior of the N-Sensor, whereby each rule had a weight of 1:

IF SN is *cutoff* THEN DR_{FIS} is *cutoff*

IF SN is *low* THEN DR_{FIS} is *high*

IF SN is *medium* THEN DR_{FIS} is *reference*

IF SN is *high* THEN DR_{FIS} is *low*

As implication method for computing the consequent fuzzy sets, *min* was chosen in MATLAB's Fuzzy Logic Toolbox (The Mathworks, 2019). It truncates the consequent membership functions at the antecedent result value. As aggregation method for combining rule consequents, *max* was used, which determines the maximum of consequent fuzzy sets. Finally, *wtaver* was chosen as defuzzification method for computing crisp output values from the aggregated output fuzzy set. It computes the weighted average of all rule outputs.

The outlined configuration only covers calibrations that lead to a theoretically possible maximum DR_{FIS} below the manually set DR_{max}. This maximum DR_{FIS} occurs at the SN_{cut} and corresponds to the value of the *high* output singleton. In case the DR_{FIS} could exceed the DR_{max} due to the calibration, it must be cut off like it is done by the N-Sensor software. For that reason, a case distinction was implemented in the algorithm. If the value for the high output singleton exceeded the DR_{max} in the first case, a new FIS was created. For the input parameter SN, three trapezoidal (*'cutoff'*, *'low'* and *'high'*) and one triangular membership function (*'medium'*) were then defined as follows:

$$Cutoff: [0\ \ 0\ \ (CF \times SN_{cut})\ \ SN_{cut}]$$

$$Low: \left[(CF \times SN_{cut})\ \ SN_{cut}\ \ \left(\frac{SN_{ref} \times SL - RR + DR_{max}}{SL}\right)\ \ SN_{ref}\right]$$

$$Medium: \left[\left(\frac{SN_{ref} \times SL - RR + DR_{max}}{SL}\right)\ \ SN_{ref}\ \ \left(\frac{DR_{min} - RR + SN_{ref} \times SL}{SL}\right)\right]$$

$$High: \left[SN_{ref}\ \ \left(\frac{DR_{min} - RR + SN_{ref} \times SL}{SL}\right)\ \ (1.5 \times SN_{ref})\ \ (1.5 \times SN_{ref})\right]$$

All the output singletons stayed the same, except *high*, to which DR_{max} was assigned. Also, the same rules as for the first case were taken. In Figure 2.5, the basic setup of the input membership functions is schematically illustrated for the second case of the algorithm.

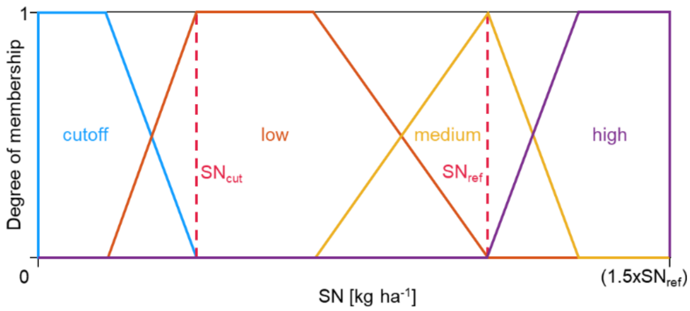

Figure 2.5. Schematic illustration of the membership function setup for the input parameter SN with *low* having a trapezoidal shape.

2.2.3.2 Simulation, optimization and validation of the model

In Table 2.1, it is indicated that the SN recordings had the widest range in data set $N3_{2NW}$. That's why its SN and DR_{YNS} recordings were used as input-output data for the optimization of the model. This was done in a trial and error procedure by simulating the DR_{FIS} using the SN values from $N3_{2NW}$, evaluating the accordance with the corresponding DR_{YNS} and adapting the CF. Trial and error methods are a common approach for designing and tuning FISs (Jahangiri et al., 2019; Sivanandam et al., 2007). For evaluation of the accordance between DR_{FIS} and DR_{YNS}, the root mean square error (RMSE) was calculated. It is a very common measure to compare measured and simulated data series and it was calculated according to:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(DR_{YNS}(i) - DR_{FIS}(i)\right)^2}{N}} \tag{2.1}$$

where i corresponds to the single measurements in the data set and N corresponds to the total number of measurements. The CF was iteratively adapted with the aim to minimize the RMSE. The procedure was stopped at a CF of 0.26.

For validation of the optimized model, simulations were performed with all data sets presented in Table 2.1. In order to enable a relative assessment of the RMSE, it was also calculated as a percentage of the mean DR_{YNS}:

$$RMSE_p = \frac{RMSE}{\frac{\sum_{i=1}^{N}\left(DR_{YNS}(i)\right)}{N}} \times 100 \tag{2.2}$$

The Pearson correlation coefficient R was calculated to assess the strength of the linear correlation between DR_{YNS} and DR_{FIS}, respectively:

$$R = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{DR_{YNS}(i)-\frac{\sum_{i=1}^{N}\left(DR_{YNS}(i)\right)}{N}}{\sigma_{DR_{YNS}}}\right)\left(\frac{DR_{FIS}(i)-\frac{\sum_{i=1}^{N}\left(DR_{FIS}(i)\right)}{N}}{\sigma_{DR_{FIS}}}\right) \tag{2.3}$$

where $\sigma_{DR_{YNS}}$ and $\sigma_{DR_{FIS}}$ correspond to the standard deviations of DR_{YNS} and DR_{FIS}, respectively.

2.2.4 Multi-parametric fuzzy expert system

2.2.4.1 Input data

A study case for $N2_3$ was created to simulate the computation of DR_{FIS} considering different constellations of SN and ECa as input parameters under specific assumptions. $N2_3$ recorded from Field 3 was chosen because of its high spatial variability in terms of the ECa values. So, the differences in the results could be contrasted more clearly. ECa measurements were chosen because they are a widely acknowledged state of the art methodology to gain patterns of soil variability at a high resolution. For the ECa, a historical data set was used that had been recorded with an EM38 (Geonics Limited, Mississauga, Ontario, Canada) ground conductivity meter in September 2007. The device had been employed in the vertical mode with depth sounding of approx. 1.5 m (Heil and Schmidhalter, 2015). As a preparatory step, the ECa data, which were available as georeferenced point values, were interpolated in a 1×1 m raster by applying Ordinary Kriging. For this, the software package ArcGIS Desktop 10.6 (ESRI Inc., Redlands, California, USA) was used. In Figure 2.6, the recorded SN measurements from $N2_3$ are shown together with the interpolated ECa map. The SN data are presented with a natural breaks classification, whereas ECa values are presented as stretched values along a color ramp. From the ECa map, the specific raster values were later on extracted at the positions of the recorded SN measurements.

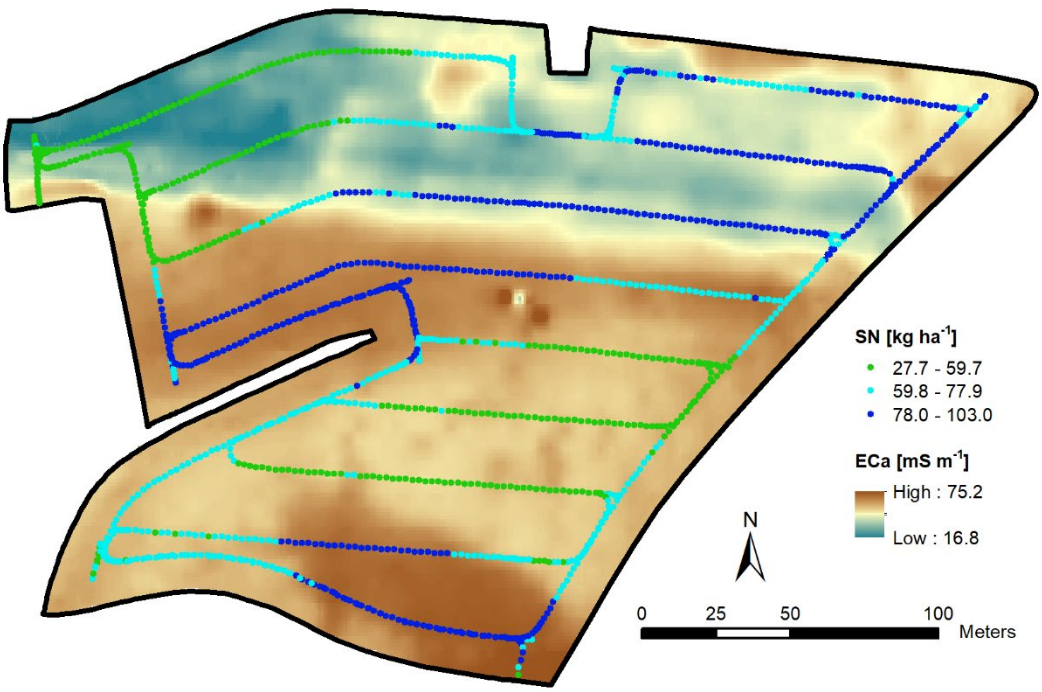

Figure 2.6. Recorded SN measurements from $N2_3$ and interpolated ECa map, where also the ECa values were extracted from.

2.2.4.2 One-parametric FISs for soil ECa

The statistics of the interpolated data set indicated a minimum ECa value (ECa_{min}) of 16.8 mS m^{-1}, a maximum (ECa_{max}) of 75.2 mS m^{-1} and a mean (ECa_{mean}) of 47.3 mS m^{-1}. In terms of the interpretation of the ECa, it was assumed in a simplified manner that the productivity potential of the soil would increase with increasing ECa values in this specific field. Two FISs were created that considered only the ECa as the input parameter to calculate the DR_{FIS}. For both, the input membership functions and output singletons were the same. Three triangular input membership functions (*'low'*, *'medium'* and *'high'*) were defined as follows:

$Low: [ECa_{min}\ ECa_{min}\ ECa_{mean}]$

$Medium: [ECa_{min}\ ECa_{mean}\ ECa_{max}]$

$High: [ECa_{mean}\ ECa_{max}\ ECa_{max}]$

In Figure 2.7, the basic setup of the membership functions for the input parameter ECa is presented schematically.

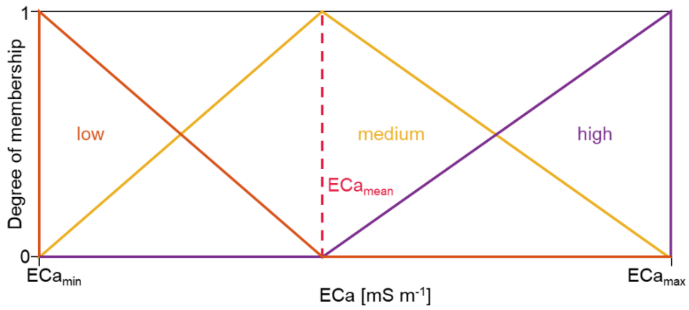

Figure 2.7. Schematic illustration of the membership function setup for the input parameter ECa.

For the output parameter DR_{FIS}, the *reference* singleton from the N-Sensor model was taken over and extended by two dedicated ones for the ECa (*'lowECa'* and *'highECa'*). To *lowECa*, a value of 0 kg ha^{-1} was assigned, whereas it was 80 kg ha^{-1} for *highECa*. This was based on the assumption that, in terms of the ECa, the expert would give less freedom in the variation of the DR_{FIS} compared to the input parameter SN.

The difference between the two FISs was characterized by the definition of the rules, whereby the rule weight was always equal to one. Two different sets were defined depending on the weather conditions around N2. Under wet conditions with the availability of a sufficient amount of water in the soil, it was assumed that the expert would like to promote the plant growth in areas of high soil productivity. Thus, the following decisions were supposed:

IF ECa is *low* THEN DR_{FIS} is *reference*

IF ECa is *medium* THEN DR_{FIS} is *reference*

IF ECa is *high* THEN DR_{FIS} is *highECa*

In case of dry weather around N2, with low water availability in the soil, it was assumed that the expert would like to reduce the N amount in areas of low productivity. Thus, the rules were set as follows:

IF ECa is *low* THEN DR_{FIS} is *lowECa*

IF ECa is *medium* THEN DR_{FIS} is *reference*

IF ECa is *high* THEN DR_{FIS} is *reference*

2.2.4.3 Parameter fusion and simulation

The FIS generated for the validation of the N-Sensor model with data set $N2_3$ served as a basis for two multi-parametric FISs and was maintained without any changes to represent the contribution of the SN to the calculation of DR_{FIS}. It was extended with the components from the one-parametric FISs for the ECa under wet and dry conditions, respectively. Thus, each of the two multi-parametric

FISs had the input parameter SN, where the membership functions were taken from the automatically set configuration of the N-Sensor model for $N2_3$. For this data set, the algorithm applied the second case of the membership function definition outlined in section 2.2.3.1. The second input parameter was ECa, where the membership functions were set in the same way as for the one-parametric FISs for the ECa. In terms of the output parameter DR_{FIS}, both multi-parametric FISs had the same singletons as the N-Sensor model for $N2_3$, extended by the two dedicated ones for the ECa. In terms of the rules, each FIS had the ones from the N-Sensor model. The distinction of the two multi-parametric FISs was finally made by extending them one time by the rules for the ECa under wet and another time by the rules for the ECa under dry conditions.

For simulations, an algorithm was developed in MATLAB, which extracted the corresponding raster value from the ECa map for every position recorded in $N2_3$. Beyond the DR_{FIS} values coming from the N-Sensor model, every recorded point of the data set was extended with further DR_{FIS} values considering only the ECa under wet and dry conditions, respectively. Second, further DR_{FIS} values were calculated considering both, the SN and the ECa, under wet and dry conditions, respectively. Finally, for every recorded point, the differences between the DR_{FIS} from the two multi-parametric systems to the N-Sensor model, as well as their differences to the respective FISs considering only the ECa were calculated. To assess the fuzzy expert system's behavior for different configurations, the simulation results were mapped. The five different DR_{FIS} results, as well as the four values indicating the differences, were interpolated within the field boundary in a raster size of 1×1 m using Inverse Distance Weighting in ArcGIS. This method was chosen due to its property as an exact interpolator. Additionally, using the raster values, the differences were quantified as absolute numbers for the whole Field 3 using MATLAB.

2.3 Results and discussion

2.3.1 Fuzzy logic-based N-Sensor model

2.3.1.1 Basic characteristic

The behavior of FISs having one input parameter can be described by a characteristic curve. In Figure 2.8, the corresponding diagram is shown for the identification data set $N3_{2NW}$, as well as data set $N2_1$. The latter is presented because it has the biggest differences to $N3_{2NW}$ in terms of the agronomic calibration. In general, the curves have a piecewise linear character and correspond to the behavior of the N-Sensor's dosing algorithm for N2 and a yield-oriented N3 in winter wheat. For SN values above the SN_{cut}, the DR_{FIS} is slightly decreasing, whereas it is strongly reduced below it. DR_{FIS} values exceeding the maximum threshold were automatically set to the DR_{max} of 120 kg ha^{-1} for $N3_{2NW}$. The basic trapezoidal shape of the characteristic curve is the same for all the validation data sets having a theoretically possible DR_{FIS} above DR_{max}. Yet, the algorithm adapted the FISs according to the corresponding agronomic calibration, which mainly affected the y-axis intercept of the section, where the DR_{FIS} is slightly reduced with increasing SN values.

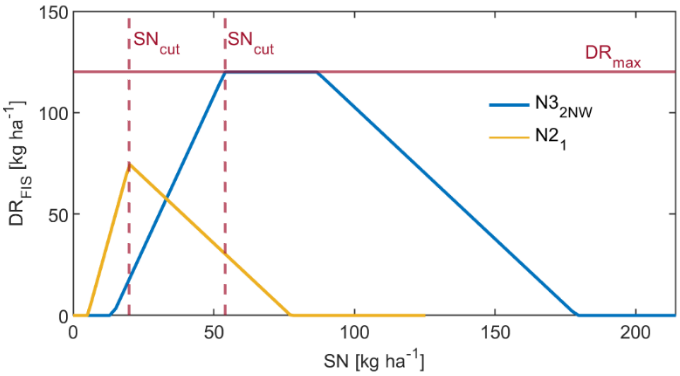

Figure 2.8. Characteristic curve of the N-Sensor model FISs for data sets $N3_{2NW}$ and $N2_1$.

$N2_1$ is a representative data set, where the maximum possible DR_{FIS} is not reaching to DR_{max}. There, the first case of the algorithm was valid, where a triangular shape was given to the low input membership function. It is apparent from Figure 2.8 that this was leading to a triangular shape of the characteristic curve. The section with a slight reduction with increasing DR_{FIS} values has the same slope as for $N3_{2NW}$, but the y-axis intercept is shifted down. It is recognizable that the DR_{FIS} values are dropping for $N2_1$ with a higher intensity for values below the SN_{cut}.

2.3.1.2 Validation results

To evaluate the performance of the fuzzy logic-based N-Sensor model, simulations were done with the data sets presented in Table 2.1. Basic statistics are shown in Table 2.2. The mean and range values for DR_{YNS} show high accordance with the ones for DR_{FIS} for each data set. Considering the values for DR_{min} and DR_{max}, it is evident from the indicated ranges that the developed algorithm could be validated at border conditions in data sets $N3_1$, $N3_{3N}$ and $N3_{3S}$. Yet, it can be seen from the SN ranges in Table 2.1 that, with $N3_1$ and $N3_{3N}$, there were only two data sets that allowed a validation for values below SN_{cut}. Comparing the mean DR_{YNS} and DR_{FIS}, respectively, with the RRs indicated in Table 2.1, the values are for some data sets deviating. The most obvious explanation for this is that the corresponding reference plot did not properly represent the average crop N-status for the affected field or subarea.

Table 2.2. Basic statistics for the identification and validation of the fuzzy logic-based N-Sensor model.

Data set	Range DR_{YNS} [kg ha $^{-1}$]	Mean DR_{YNS} [kg ha^{-1}]	Range DR_{FIS} [kg ha^{-1}]	Mean DR_{FIS} [kg ha^{-1}]
Identification				
$N3_{2NW}$	0 – 120	34.7	0 – 120	34.7
Validation – N2				
$N2_1$	2.8 – 72.4	32.4	2.8 – 72.4	32.4
$N2_2$	9.8 – 109.5	55.3	9.7 – 109.6	55.3
$N2_3$	14.6 – 112.5	56.8	14.7 – 112.5	56.8
Validation – N3				
$N3_1$	43.6 – 120	79.8	43.7 – 120	79.8
$N3_{2SE}$	18.6 – 112	44.1	18.5 – 112	44.1
$N3_{3N}$	63 – 120	93.9	63 – 120	93.9
$N3_{3S}$	0 – 55.9	25.1	0 – 55.9	25.1

Also, the statistical key figures introduced in 2.2.3.2 underline the high accordance of DR_{FIS} and DR_{YNS}, as well as the good adaption of the algorithm to different conditions. All R values were above 0.99 and all the results for the RMSE had a value of 0.04 kg ha^{-1}. Consequently, the $RMSE_p$ was indirectly proportional to the mean DR_{YNS}. The maximum value was reached for $N3_{3S}$ with 0.14%. From a practical point of view, these errors can be considered as negligible for two main reasons. First, it is very unlikely that the agronomical effect of a variation of the N fertilizer dosing in this magnitude can be detected at all. Second, there are several error sources in the spreading process that are likely to cause more error (e.g. a limited accuracy of the spreader's metering system and external error sources like wind influencing the distribution on the field).

2.3.2 Simulation of the multi-parametric fuzzy expert system

2.3.2.1 Characteristics and numerical simulation results

With data set $N2_3$, simulations were performed using different constellations of SN and ECa as input parameters. The characteristic diagrams of the corresponding FISs are shown in Figure 2.9. In every case, the DR_{FIS} was the only output parameter. Figure 2.9a shows the behavior of the FIS considering only the SN as an input parameter. The diagram originates from the validation of the fuzzy logic-based N-Sensor model and its basic shape is the same as for the identification data set $N3_{2NW}$ shown in Figure 2.8. It is apparent that for $N2_3$, the curve is only slightly touching DR_{max}. For Figure 2.9b and c, the ECa was considered as the only input parameter, whereby for b, the rules were set in a way to respond to wet weather conditions and for c, they reflected a response to dry weather conditions. Both diagrams could be approximated by a stepwise linear function. As expected, the course of the diagrams is opposite to each other. Figure 2.9d and e show the FIS characteristics for a fusion of both input parameters assuming wet and dry conditions, respectively. Apparently, the behavior depending on the SN values is similar as in Figure 2.9a. Yet, the characteristic curve is virtually compressed. While the SN values at the shoulders and bases of the triangular shape stayed the same, their corresponding DR_{FIS} values changed and therefore the slope for SN values beyond SN_{cut}. With the ECa, the characteristics depending on the SN are expanded by a third dimension, which is reflecting the behavior shown in Figure 2.9b and c, respectively. But also here, the slopes and absolute values are different. So, the parameter fusion found a compromise between the characteristics depending on only one input parameter.

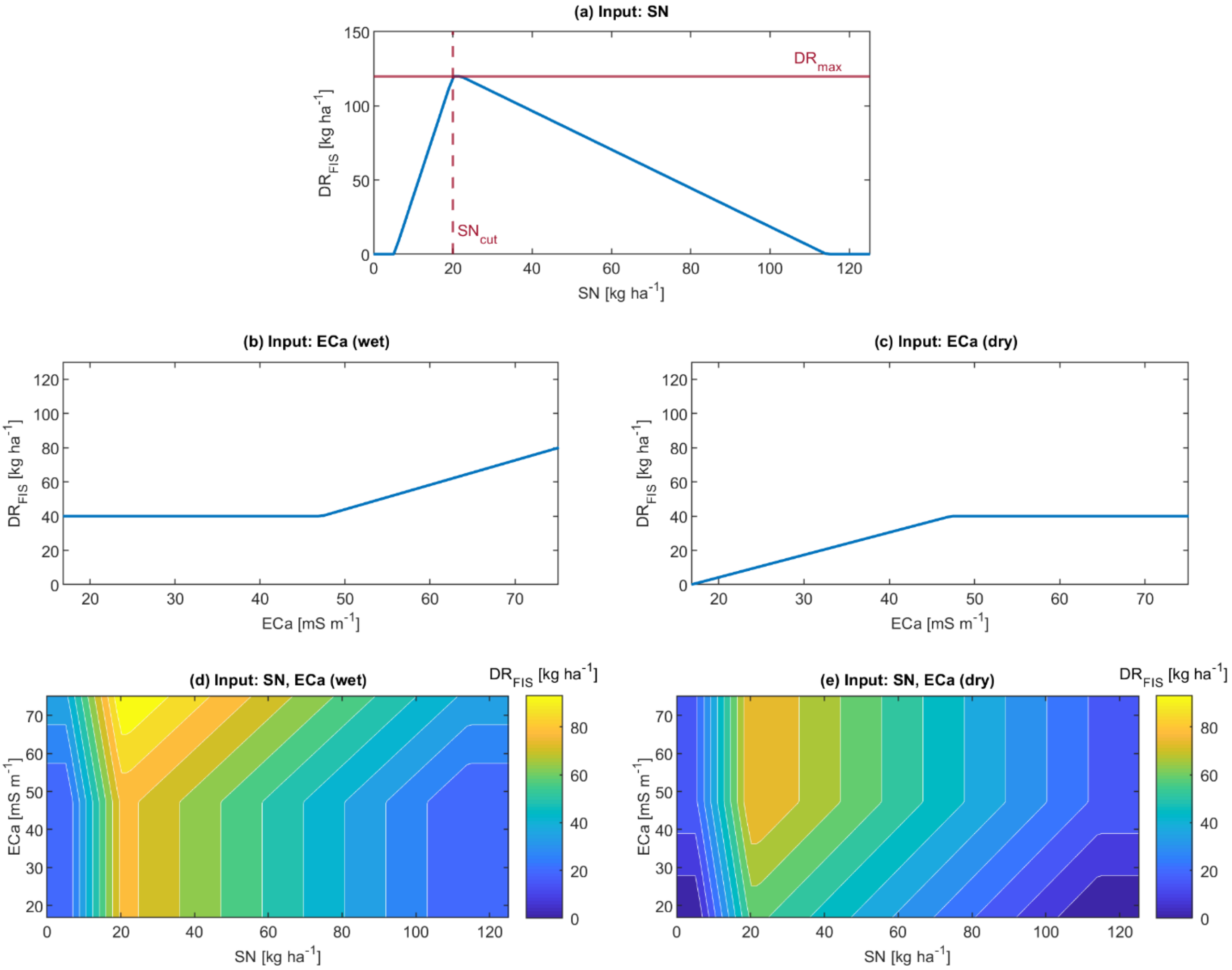

Figure 2.9. FIS characteristics for the data set N2$_3$ (a) N-Sensor model having only SN as input parameter (b) having only ECa as input parameter and assuming wet conditions (c) having only ECa as input parameter and assuming dry conditions (d) fusion of both input parameters and assuming wet conditions (e) fusion of both input parameters and assuming dry conditions.

In Table 2.3, the simulation results are expressed with the ranges and mean values of the outputted DR$_{FIS}$. For the N-Sensor model, the mean value exceeds the RR of 40 kg ha^{-1} and the most likely reason for this is the choice of a reference plot, which had a higher SN than the mean of the field. For the sole consideration of the ECa, the DR$_{FIS}$ did not fall below the RR for wet conditions, whereas RR was the maximum for dry conditions. This fits the characteristics presented in Figure 2.9b and c. Assuming an approximately normal distribution of the ECa data, it is also clear then why the mean DR$_{FIS}$ value is exceeding the RR for wet conditions and is falling below it for dry conditions. An explanation for the different gap of the mean values to the RR is that the ECa$_{min}$ and ECa$_{max}$ values do not have the same difference to ECa$_{mean}$. The discrepancies in terms of mean DR$_{FIS}$ and its range between the N-Sensor model and the one-parametric FISs considering the ECa only are higher under dry conditions. This is most likely because the behavior depending on the ECa is then most contradictory to the behavior depending on the SN.

Table 2.3. Numerical results from the simulation of the multi-parametric fuzzy expert system.

Input parameters	Range DR_{FIS} [kg ha $^{-1}$]	Mean DR_{FIS} [kg ha^{-1}]
SN	14.7 – 112.5	56.8
ECa (wet)	40 – 71.6	47.2
ECa (dry)	0.6 – 40	33.9
SN, ECa (wet)	31 – 80.3	52
SN, ECa (dry)	23.1 – 76	45.4

For the multi-parametric FIS under wet conditions, the range of DR_{FIS} was narrowed compared to the N-Sensor model. An explanation for this is that there was more freedom to change the DR_{FIS} depending on the SN than on the ECa, which was already outlined in chapter 2.2.4.2. The same counts for the DR_{FIS} range of the multi-parametric FIS under dry conditions, which is similar to the one under wet conditions, yet slightly pulled down. This can be explained by the fact, that the behavior depending only on the ECa is virtually mirror-inverted under wet and dry conditions, respectively. The mean DR_{FIS} values of the multi-parametric systems are smaller than the mean DR_{FIS} from the N-Sensor simulation, indicating that the overdosing effect due to the choice of the reference plot was minimized with the multi-parametric FISs. However, they are higher compared to the one-parametric FISs considering the ECa only, showing that in the multi-parametric FISs a compromise was found between the contrary reasoning of the dedicated one-parametric systems.

2.3.2.2 Mapped simulation results

The interpolated simulation results in terms of the DR_{FIS} are presented in Figure 2.10. The results for the N-Sensor model are presented in Figure 2.10a, whereby low DR_{FIS} values correspond to high SN values indicated in Figure 2.6 and high DR_{FIS} values correspond to low SN. In Figure 2.10b and c, the mapped DR_{FIS} results solely depending on the ECa are shown. Under wet conditions, the distinct area of lowest ECa values, which can be identified from Figure 2.6, has a uniform DR_{FIS} at the level of RR, whereas the rest of the field has a higher DR_{FIS}. Under dry conditions, this distinct area has values below the RR, whereas large parts of the remaining area have the RR as DR_{FIS}. There is an area in the very south, which would get the highest DR_{FIS} under wet conditions, whereas under dry conditions, there is an area in the north-west, which would get the lowest DR_{FIS}. Both areas match with conspicuous areas in Figure 2.10a. Yet, they are interpreted contradictory to the N-Sensor model, which should not be considered as erroneous behavior. Although single-parametric systems are providing a substantial basis towards site-specific application, it is not possible for them to precisely define the dose rates that need to be applied since this is the outcome of a complex process involving multiple factors.

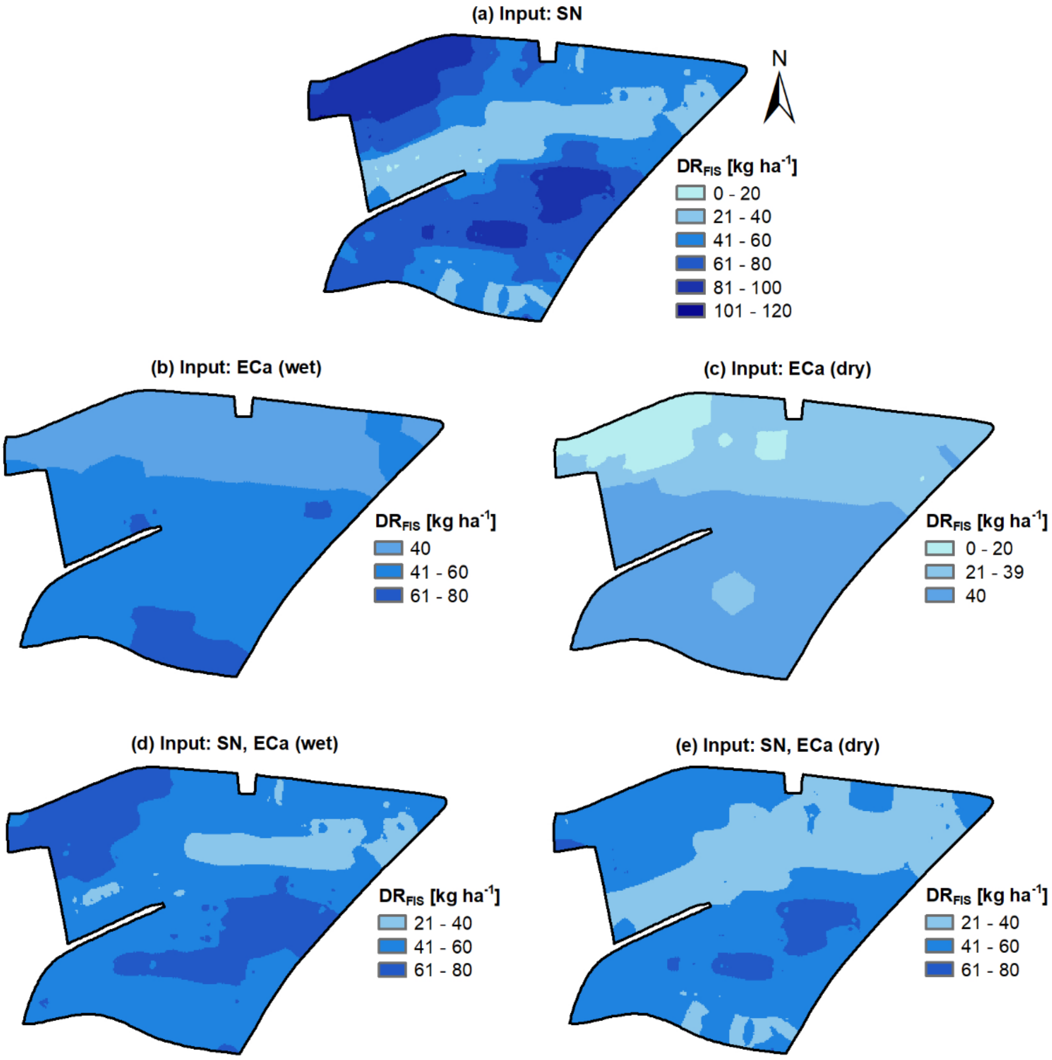

Figure 2.10. Mapped results from the simulation of the multi-parametric fuzzy expert system. (a) N-Sensor model considering only SN as input parameter, (b-c) considering only ECa as input parameter under wet and dry weather conditions, respectively, (d-e) considering both parameters under wet and dry weather conditions, respectively.

Figure 2.10d and e show the effect of a fusion of both input parameters under different weather conditions. Under wet conditions, the areas with a high DR_{FIS} from the N-Sensor model remain in parts pronounced, whereby they are significantly moderated to Figure 2.10a in terms of the absolute DR_{FIS} values. In general, the DR_{FIS} is balanced towards medium values. An apparent indication for this is the area of comparatively high DR_{FIS} in Figure 2.10b. It is moderated with values closer to the RR, which is showing that the parameter fusion harmonized the contradictory reasoning from the N-Sensor model and the one-parametric FIS considering the ECa only. Under dry conditions, the large area in the mid having low DR_{FIS} values in Figure 2.10a is enlarged, whereas the spots of high DR_{FIS} are strongly shrunk in terms of size and DR_{FIS} values. Analogously to the wet conditions, the multi-parametric fusion again found a compromise at areas, where the results from the single-parametric FISs were drifting apart from each other. The results imply that the multi-parametric FISs can respond to remaining uncertainties in terms of the interpretation of the single parameters.

With the difference maps presented in Figure 2.11, the contrast of the multi-parametric systems to the one-parametric approaches is highlighted even more. Positive values are indicating higher DR_{FIS} values from the respective multi-parametric system, and thus a DR_{FIS} increase compared to the N-Sensor model or the corresponding FISs considering the ECa only. Negative values are therefore implying a DR_{FIS} reduction. Figure 2.11a and b show the differences in DR_{FIS} between the N-Sensor model and the multi-parametric FISs. Considering also the pattern of Figure 2.10a, there is an increase of the DR_{FIS} in areas of high SN under wet conditions, which is implying that the multi-parametric approach would expect more potential in these areas than the N-Sensor model due to favourable conditions in terms of water availability for the crop. In areas of lower SN, the DR_{FIS} is decreased. So, the multi-parametric FIS is, in turn, damping the expectations of the N-Sensor model to gain more benefit by increasing the DR. As outlined in chapter 2.3.2.1, this pattern is also reflecting again the effect of the differing freedom in terms of changing the DR_{FIS}, which was given in the output singleton definition to each parameter. Under dry conditions, the reduction of DR_{FIS} in the areas of low SN is even much stronger. The areas, where there is an increase compared to the N-Sensor model are significantly shrunk. With the ECa, the multi-parametric approach contains a component that is retracting the DR_{FIS} due to assumed unfavourable conditions in terms of water availability for the crop. Consequently, there are large areas, where the multi-parametric FIS is outputting remarkably less DR_{FIS}.

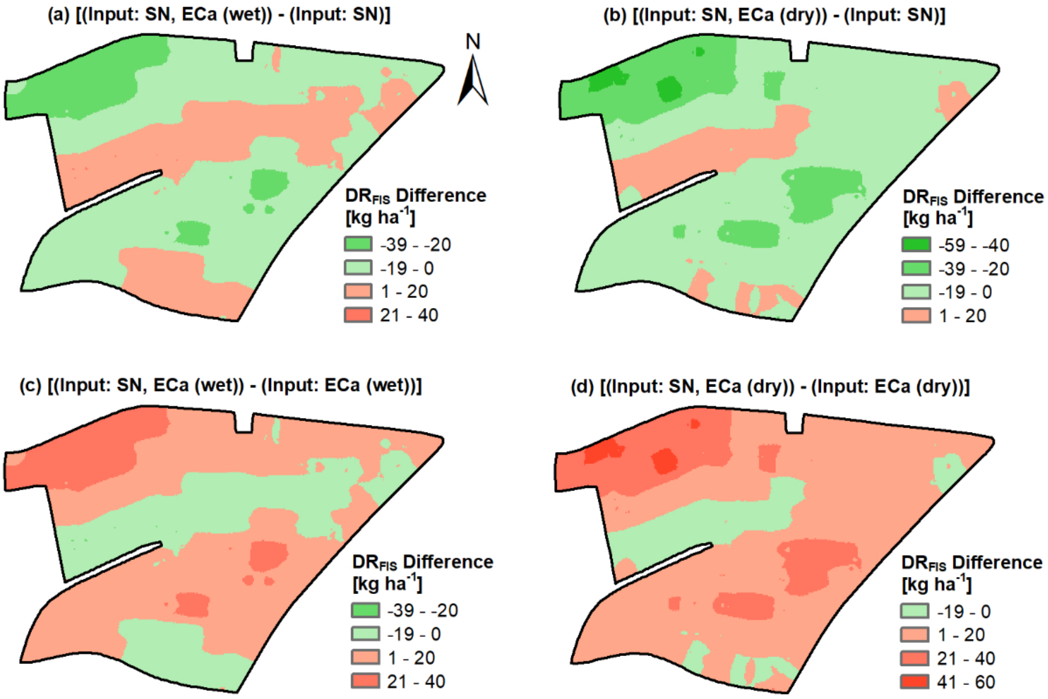

Figure 2.11. Mapped DR_{FIS} differences of multi-parametric FISs to the one-parametric ones, (a-b) showing the differences to the N-Sensor model under wet and dry conditions, respectively, (c-d) showing the differences to a sole consideration of the ECa under wet and dry conditions, respectively.

The differences in terms of the outputs of the multi-parametric FISs compared to the FISs considering the ECa only are shown in Figure 2.11c and d. It is striking that the patterns seem to be exactly the same as the ones shown in Figure 2.11a and b. However, they are virtually mirror-inverted. So, areas that previously corresponded to a reduction compared to the N-Sensor model now correspond to increases compared to the respective one-parametric FIS considering the ECa only, and vice versa. Under wet conditions, the multi-parametric FIS would in large parts grant for more fertilizer than the one-parametric approach. The effect is reinforced under dry conditions, which is reasonable in front of the background that the asymmetric behavior of the FIS considering the ECa only is inevitably leading to DR_{FIS} values below or at the level of RR. Here, it becomes apparent that the multi-parametric approach can catch a drop in DR_{FIS}, if the plant-related component is reasoning for an increased DR_{FIS}. For the wet, as well as for the dry scenario, again the fact comes to play that in the N-Sensor model the choice of a reference plot with a comparatively high SN has led to a drift of DR_{FIS} towards values higher than the RR. In parts, the multi-parametric FIS is consequently reflecting this behavior.

Table 2.4 indicates the absolute reductions and increases of kg N in Field 3 when comparing the multi-parametric FISs to the one-parametric ones. The numbers are derived from the raster values of the interpolated difference maps and represent a quantification of the patterns shown in Figure 2.11

and described above. Considering the differences to the N-Sensor model, one can state that on a field level, the reductions predominate. They are significant in front of the background that the total applied amount of N on Field 3 would have been 275.7 kg with the N-Sensor model, and 192 kg with a uniform application of the RR. Compared to the FISs considering the ECa only, the increases are consequently higher than the reductions. Once more, this indicates that the multi-parametric FISs can harmonize the partly contrary and biased behavior of the dedicated one-parametric systems.

Table 2.4. Simulated differences of the multi-parametric FISs compared to the one-parametric FISs, expressed in total N on Field 3.

Input parameters	Total N reduction [kg]	Total N increase [kg]
[(Input: SN, ECa (wet)) – (Input: SN)]	38.1	12.5
[(Input: SN, ECa (dry)) – (Input: SN)]	60.2	2.9
[(Input: SN, ECa (wet)) – (Input: ECa(wet))]	12.5	38.1
[(Input: SN, ECa (dry)) – (Input: ECa(dry))]	2.9	60.2

2.4 Conclusions

Using a Yara N-Sensor ALS2 real-time sensor system, data were acquired for the cases of N2 and yield-oriented N3 in winter wheat. The dosing algorithm of the sensor software was modeled with a Takagi-Sugeno FIS using one set of input-output data. The newly developed algorithm was validated with seven further data sets. The validation has shown that the algorithm could automatically adapt the input membership functions and output singletons of the FIS to a wide range of settings because there was high accordance with the behavior of the N-Sensor's dosing algorithm. With the use of fuzzy logic, the latter was translated into a form that allows the fusion with further agronomic parameters in a straightforward manner. Furthermore, by being well adapted to the perception and reasoning of a human, it is even possible for an expert to modify the algorithm based on the underlying circumstances of a specific application.

For a multi-parametric fuzzy expert system, a study case in N2 was created. Based on specific assumptions in terms of the agronomic interpretation of the soil ECa, two one-parametric FISs were set up, which considered it as the only input parameter to derive a dose rate under different weather conditions. Two further FISs were created, where the model of the N-Sensor dosing algorithm was combined with these. With the N-Sensor model, the presented multi-parametric systems contain a generic part that is supplemented by the soil ECa and weather information. The presented approach allows them to be interpreted by an expert for each specific field and application. This is done by adapting the corresponding input membership functions, output singletons, rules and rule weights. Simulations with an N-Sensor recording and historic ECa data have shown that the decisions depending only on one parameter can be refined with a fusion in a multi-parametric system. The underlying case distinction between wet and dry conditions was implemented with a simple adaption of the rules affecting the ECa. The simulation results implied that multi-parametric fusion is more robust and can find a compromise between the one-parametric systems and thus minimize the risk of partly undesired behavior due to their specific deficiencies. The presented modular approach also provides high flexibility in terms of the target orientation affecting e.g. environmental or economic aspects.

Further development of the fuzzy logic-based N-Sensor model should encompass the transfer to a wider range of different settings for DR_{min} and DR_{max}, as well as different calibrations and application scenarios like a quality-oriented N3. With further efforts in terms of the agronomic interpretation of the input parameters, the presented methodology could be enhanced with further inputs, like e.g. topography or further soil analysis techniques. With the rule weights, the expert could take into account the specific relevance of an input parameter. This could be necessary in cases where e.g. the variability of single parameters in the field is significantly differing. Future work should deal with the implementation of the presented methodology in a fuzzy control to fuse multiple parameters with the N-Sensor data in real-time. Also, the usability should be improved by capturing the expert's decision in a user-interface without the participation of a knowledge engineer. The approach should be tested in agronomic trials to quantify the potential benefits based on the target orientation defined by the expert.

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CHAPTER 3

Paper B

Real-time control for multi-parametric data fusion and dynamic offset optimization in sensor-based variable rate nitrogen application[2]

Andreas Heiß, Dimitrios S. Paraforos, Galibjon M. Sharipov and
Hans W. Griepentrog

Abstract

Real-time sensor systems for variable rate nitrogen (N) application (VRNA) are an established technology nowadays but they have some shortcomings in terms of their capability to consider multiple parameters relevant for plant growth. Further, the abundantly lacking section control in centrifugal spreaders limits the accuracy of a sensor-based VRNA, especially in combination with the temporal and spatial offsets between sensing and fertilizer placement.

Fuzzy inference systems were incorporated into a real-time control to numerically fuse the crop N uptake sensed by a real-time sensor system, as well as mapped soil electrical conductivity (ECa) data for the calculation of site-specific N dose rates (DR). A distinction of two subsections within the working width of a sensor-spreader system was made based on the ECa data. Further, by implementing a generic model, the control system agronomically optimized the rate control of a centrifugal spreader in order to compensate positional lags and technical latencies and minimize the spatial offset between DR determination and application in a dynamic manner.

With field tests at different driving speed scenarios going partly beyond the usual operation conditions, the real-time control was verified. The differentiation of the sections has resulted in slight

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DR differences, whereas the control system has shown a high consistency in calculating the DRs and sending commands to the spreader in a coordinated manner. The level of spatial concordance between DR determination and application had a highly stochastic character. However, the deviation was never beyond 1.5 m and the percentage of deviations beyond 1 m reached a maximum of 2.3% among the different recorded datasets, which can be considered as a sufficient performance for practical needs.

Keywords: variable rate application, real-time sensor systems, multi-parametric data fusion, application accuracy, ISOBUS

Nomenclature

D	Tractor's wheel based machine distance, m
d_1	Lateral offset of the spread pattern's focal points to the longitudinal axis, 5.6 m
d_2	Longitudinal offset of the spread pattern's focal points to the spreading disc centers, 14.7 m
d_3	Longitudinal offset of the GNSS antenna to the spreading disc centers, 2.1 m
d_4	Longitudinal offset of the GNSS antenna to the N-Sensor traverse, 0.5 m
D_e	Target wheel based machine distance, m
d_i	Dynamic longitudinal offset between dose rate determination and corresponding application, m
DR	N dose rate, kg ha^{-1}
ECa	Apparent electrical conductivity, mS m^{-1}
g	Acceleration of gravity, 9.81 m s^{-1}
h	Height of fertilizer fall, 0.14 m
i	Index for main processing cycles of the real-time control
j	Index for timers existing at i in the timer cache
k	Index for started timer that had been created in i
$P(x\|y)$	UTM coordinates of the GNSS antenna, m
$P^*(x^*\|y^*)$	Projected UTM coordinates of P, m
P_{fl}	Left focal point of the spread pattern
P_{fr}	Right focal point of the spread pattern
$P_l^*(x_l^*\|y_l^*)$	Projected UTM coordinates of left query point, m

$P_p^*(x_p^*\|y_p^*)$	Projected UTM coordinates of center point between the spread pattern's left and right focal points, m
$P_r^*(x_r^*\|y_r^*)$	Projected UTM coordinates of right query point, m
$P_s^*(x_s^*\|y_s^*)$	Projected UTM coordinates of center point between the left and right query point, m
q	Fertilizer mass flow, kg min^{-1}
$r_{s,j}$	Fertilizer SR deposited in timer j, kg ha^{-1}
r_t	Most recent SR with transmission to the spreader being verified, kg ha^{-1}
s_d	Spacing between spreading discs, 1.1 m
SN	Normalised sensor value corresponding to crop N uptake, kg ha^{-1}
SR	Fertilizer setpoint rate, kg ha^{-1}
t_a	Actuator setting time, s
t_d	Delay time for timer start, s
t_f	Time for fertilizer to fall on spreading disc, 0.17 s
t_{GNSS}	UNIX system time at reception of GNSS coordinates, s
t_{SN}	UNIX system time at SN value reception, s
v	Tractor's wheel based speed, m s^{-1}
w	Working width, m
ε	Deviation between point of DR determination and corresponding point of application, m
μ_a	Mean value of normal distribution fitted to the angular fertilizer distribution, 19°
μ_r	Mean value of normal distribution fitted to the radial fertilizer distribution, 15.5 m
ψ	Tractor's heading, rad

3.1 Introduction

A main reason for low recovery rates in mineral nitrogen (N) fertilization and associated adverse environmental effects is the usually uniform application, which does not meet the spatially varying needs of the crop (Balafoutis et al., 2017; Shanahan et al., 2008). Variable rate N application (VRNA) addresses the prevailing spatial heterogeneities and can mitigate negative external effects (Argento et al., 2020; Griepentrog and Kyhn, 2000). However, the agronomic algorithms used for VRNA are subject to controversial discussions and its implementation with common applicators has significant limitations in terms of the application accuracy.

Real-time sensor systems assessing the crop's current N status by means of spectral measurements are one of the most established VRNA technologies. Conceptual considerations to combine real-time sensor with mapped information were formulated by Auernhammer (2001). Still, today's systems usually only consider the N supply of the crop, even though plant growth and yield formation are complex processes influenced by the interaction of various biotic and abiotic factors causing also temporally dynamic variabilities (Griepentrog et al., 2007; Schmidhalter et al., 2008). The soil apparent electrical conductivity (ECa) is an established parameter to consider soilborne factors and it is frequently suitable for delineating zones of different soil productivity (Adamchuk et al., 2011; Anderson-Cook et al., 2002). Even its dependencies with various edaphic factors and especially the water and clay content are well researched, the implications on crop growth and yield are not straightforward and partly opposite, which requires the consideration of local conditions for its interpretation (Heil and Schmidhalter, 2017; Kitchen et al., 2003). To be more responsive to the complexity of N management, Heiß et al. (2021) presented a methodical basis to combine real-time sensor, weather, as well as ECa information in a multi-parametric fuzzy expert system for VRNA. Specifically in terms of the ECa, the approach was based on a situation-related interpretation of an agronomic expert as suggested by Martínez-Casasnovas et al. (2018).

Ostermeier et al. (2003) and (2007) defined a conceptual framework for the incorporation of an expert system for VRNA based on real-time multi-sensor data fusion within the bus communication networks of agricultural machinery. The latter are increasingly designed according to the ISO 11783 standard (commonly designated as ISOBUS), which defines meanwhile the possibility of using fused real-time and mapped information in peer control (Paraforos et al., 2019). The interaction of different subsystems for a real-time VRNA necessarily raises questions about the required precision of the application process. Focussing on the heterogeneities prevailing at the field scale, Thiessen (2002) found that these are mostly beyond common working widths of 24 m. In contrast, Griepentrog et al. (2007) concluded that the magnitude of the variability to be targeted does not justify applicator working widths of more than 20 m.

With dedicated setpoint rates of fertilizer (SR) for each spinning disc, the resolution of VRNA can be enhanced in off-centerline centrifugal spreaders in a straightforward manner (Griepentrog and Persson, 2000). These spreaders are up today by far the most common applicators for granular fertilizer in Europe (Nørremark et al., 2017) and they have faced significant technical progress in recent years. Also, research is focussing on their further enhancement with e.g. optimal control techniques (Rußwurm et al., 2020). To minimize application errors as examined by Sharipov et al. (2021), the spatial discrepancy between sensed spot and application area needs to be considered. Like in all variable rate application systems, this involves also single latencies of different system components and sub-processes, as well as their interaction (Bennur and Taylor, 2010). Research was conducted on modeling the setting time of dosing actuators (Carrara et al., 2005) and implementing control sequence optimization to improve variable rate fertilization accuracy (Zhang and Liu, 2022). Compensation of the positional lag was realized with static time offsets (Yinyan et al., 2018) or considering the GNSS based speed (Partel et al., 2021). A dynamic model to optimize the temporal and spatial offsets between rate determination and application in centrifugal spreaders was presented by Griepentrog and Persson (2001). The control implementation of such a model would allow considering the driving speed as a further parameter, which could be advantageous in VRNA (Hofstee, 1995).

The outlined aspects of N dose rate (DR) calculation and precise fertilizer application represent two core challenges of sensor-based VRNA that were addressed in a research project. Its specific aims were significant enhancements by numerically fusing multiple parameters relevant for plant growth with the aid of the fuzzy expert system presented by Heiß et al. (2021) and increasing the precision of the application system with a combination of section control and dynamic offset optimization, which should compensate also the inherent technical latencies. A real-time controller platform was developed to bundle the necessary algorithms. Different test series were defined to verify the system using historic SN and ECa data. The main novelties of the presented approach lie in (1) the control implementation of a numeric real-time fusion of crop N and soil ECa information in a fuzzy inference system (FIS) to define DRs on-the-go, (2) the increase of resolution by defining two sections (left and right) within the data fusion and application system and (3) the optimized rate control of the spreader to ensure the spatial concordance of DR determination and application for both sections under dynamic conditions.

3.2 Materials and methods

3.2.1 Instrumentation

The developed real-time control was embedded into a state of the art sensor-tractor-spreader system, which is presented in Figure 3.1. A Fendt 516 Vario tractor (AGCO GmbH, Marktoberdorf, Germany) was used, which was equipped with an Autopilot steering system using position data from the integrated RTK-GNSS (Trimble Inc., Sunnyvale, CA, USA). The latter's accuracy is indicated with ±2.5 cm by the manufacturer. Together with the GNSS antenna, an N-Sensor ALS2 system (YARA GmbH & Co. KG, Dülmen, Germany) was mounted on the tractor's roof. It was operated with the N-Sensor 4.5 software installed on a laptop with a 64-bit Windows 10 Pro operating system, equipped with an Intel Core i5-8250U at 1.6 GHz processor and 8 GB working RAM. The N-Sensor software was supplied with position data received at 5 Hz from the tractor's RTK-GNSS via a serial communication port. The same laptop was used also as a controller platform for real-time control. Furthermore, an AXIS-H 30.2 EMC+W two-disc centrifugal spreader (RAUCH Landmaschinenfabrik GmbH, Sinzheim, Germany) following the off-center-line principle was attached at the tractor's rear hitch. It was equipped with a mass flow control considering the current driving speed, as well as the actual measured mass flow and operated with the universal virtual terminal function of a CCI1200 terminal (Competence Center ISOBUS e.V., Osnabrück, Germany). The tractor, spreader, as well as terminal, were connected via the ISOBUS network communication.

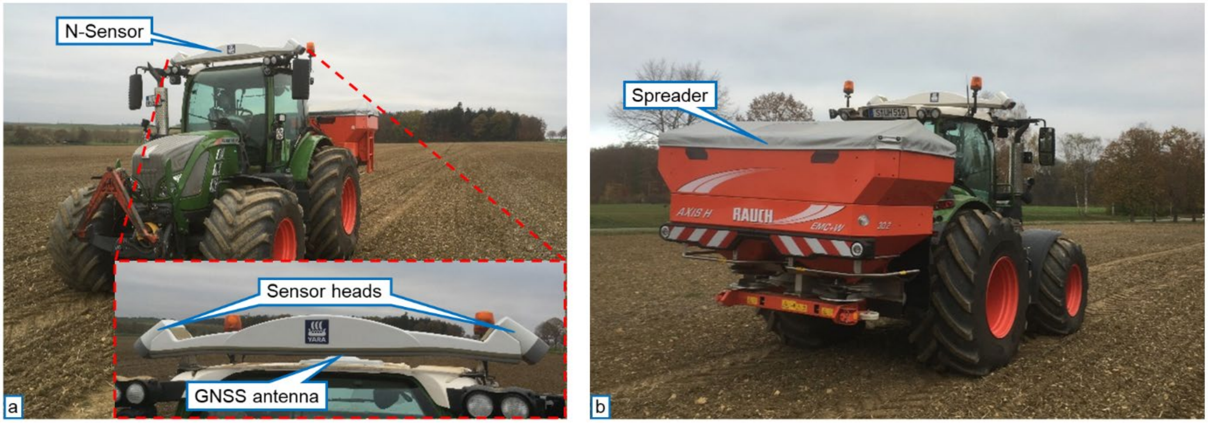

Figure 3.1. Instrumentation used for field experiments. (a) showing tractor and N-Sensor and (b) showing the spreader.

3.2.2 Fuzzy inference systems

As N fertilization offers in general only a short time window during the growing season for experimentation, testing and evaluation of the real-time control were conducted using input data that had been recorded in the scope of a real N application on an experimental field ('Riech Nord') at the research farm 'Ihinger Hof' of the University of Hohenheim (48°44'41.61''N, 8°55'26.42''E). Data acquisition took place in spring 2020, where the whole field was cultivated with winter wheat (*Triticum aestivum L.*). To be close to field capacity and thus eliminate the influence of soil moisture, ECa data were acquired just before the first split N application, in March 2020. An EM38 ground conductivity meter (Geonics Limited, Mississauga, ON, Canada) was used at the horizontal mode, where the depth sounding was approximately 0.75 m (Heil and Schmidhalter, 2015). In total, 2 381 data points were recorded by following lines with a spacing of approximately 6 m, whereby there was a shift of 3 m compared to the fixed 24 m tramlines to avoid any influence of soil compaction. In Figure 3.2a, the acquired ECa raw data are presented together with a corridor of 15 m along a subsoil water supply pipeline. The latter laid at a depth of approximately 1.2 m and thus should not have had a significant influence on the ECa readings. Consequently, the drift towards higher ECa values within the corridor was most likely caused by a disturbance of the soil structure. Due to that drift, the subsequent ordinary kriging with ArcGIS Desktop 10.6 (ESRI Inc., Redlands, CA, USA) was conducted in two steps. First, the underlying geostatistical model was defined without considering the data points within the corridor to represent the inherent pedological pattern of the field. Second, this model was applied on all data points to conduct an interpolation in a 1 × 1 m raster.

N-Sensor measurements were conducted just before the second split N application, in April 2020, at Zadoks growth stage 31 (Zadoks et al., 1974). A reference N rate of 80 kg ha^{-1} was defined by an agronomic advisor, which corresponded to 296 kg ha^{-1} of the used calcium ammonium nitrate fertilizer. The same N-Sensor software calibration and data acquisition process was conducted as described in detail by Heiß et al. (2021). Here, also detailed information on the N-Sensor system's working principle can be found. In Figure 3.2b, the boundary of the experimental field is presented together with the interpolated ECa and the recorded point data of the normalized sensor value (SN), which corresponds to the N uptake of the crop in kg ha^{-1}. Beyond that, a geofence taken from the national soil inventory is indicated, where there was a switch to another FIS with a dedicated configuration. Finally, two tramlines A and B are shown, which served as measurement tracks for the experiments with the real-time control.

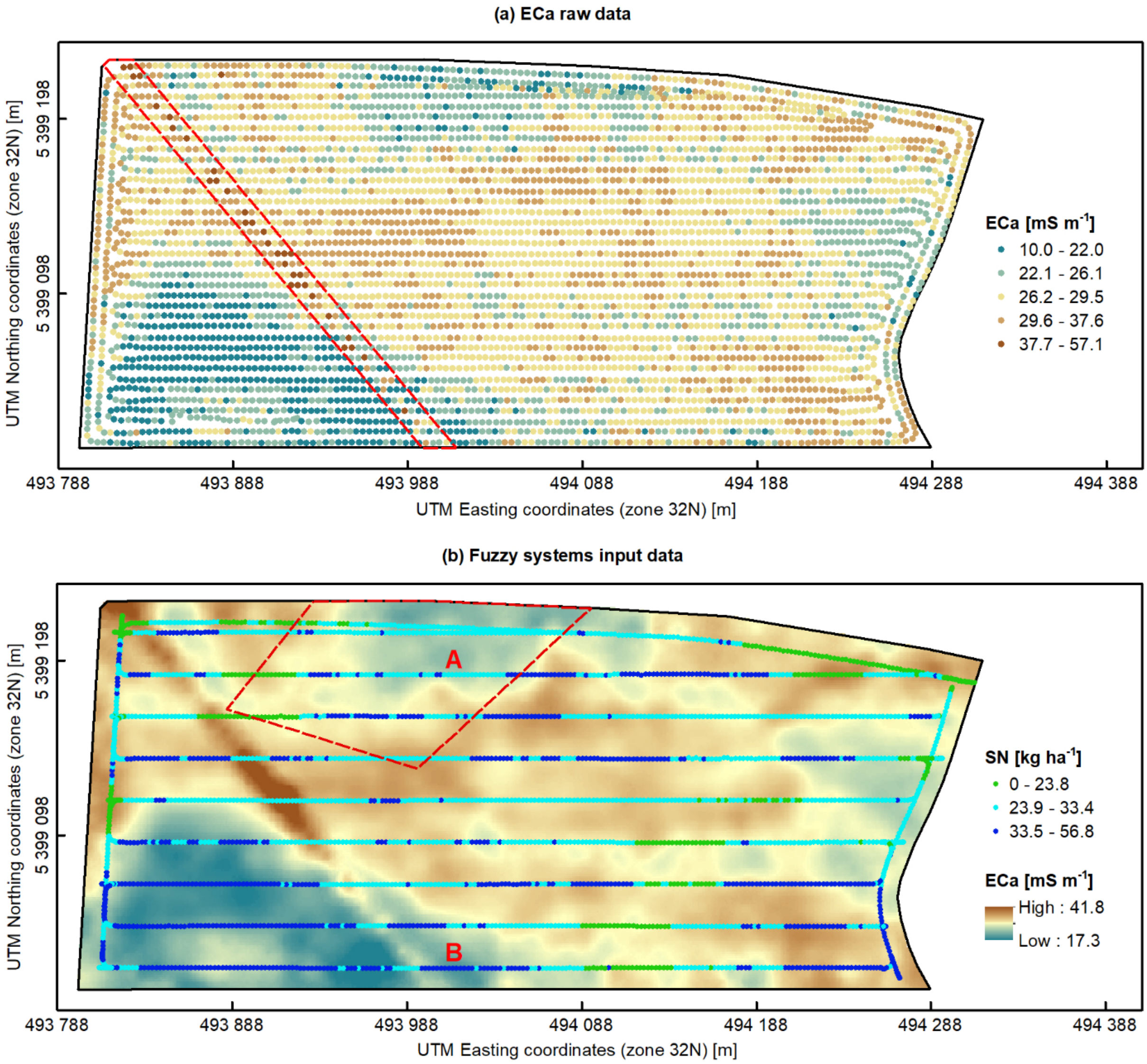

Figure 3.2. Maps of the experimental field with (a) showing the acquired ECa raw data and the corridor along the water pipeline (red dashed line) and (b) showing the interpolated ECa and recorded SN data, indications for the examined tracks A and B, as well as the geofence (red dashed line).

As one of the main subsystems of the real-time control two multi-parametric FISs were set up for the case of the second split N application using the fuzzy logic toolbox of MATLAB R2019a (The Mathworks Inc., Natick, MA, USA). One of them was a dedicated FIS for being used within the geofence and the other one was used as default FIS for the rest of the field. Both were composed of two one-parametric FISs as presented already by Heiß et al. (2021), whereby the fuzzy logic-based imitation of the N-Sensor's dosing algorithms was slightly enhanced and the interpretation of the ECa in terms of the DR was adapted to the experimental field based on the assessment of the farm manager and an agronomic advisor. The resulted characteristics of the multi-parametric FISs are shown in Figure 3.3. On both subplots, the behavior of the DR depending on the SN basically corresponds to the behavior of the N-Sensor with a slightly compressed characteristic curve. With the ECa, the DR characteristic depending on the SN is extended by a further dimension. In Figure 3.3a, it can be seen that for the default multi-parametric FIS, the characteristic is reflecting the intended relocation of the DR from high to low ECa values. On the other hand, the characteristic for the dedicated FIS for the geofence, which is presented in Figure 3.3b, indicates no DR variation according to the ECa, which is reflecting the intention that the N fertilization should react with reduced DRs to the overall low soil productivity assumed within this area.

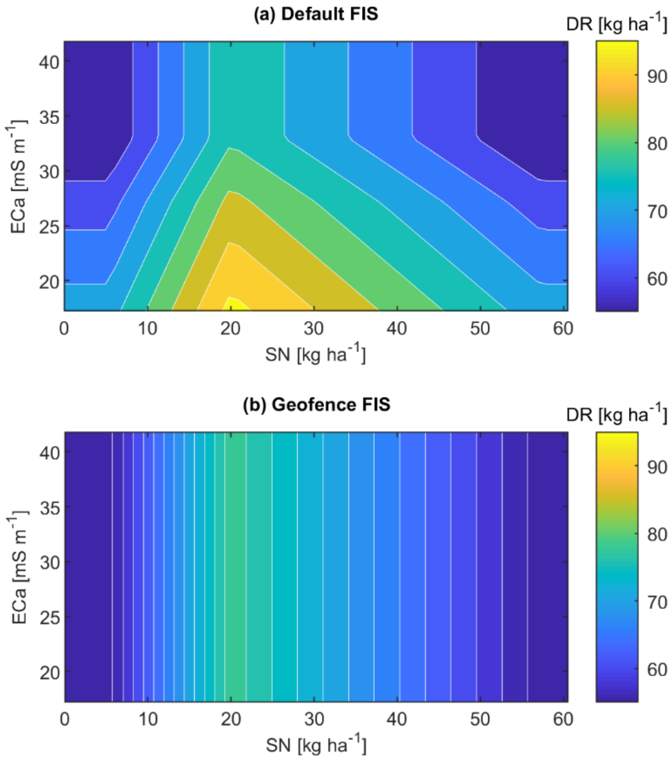

Figure 3.3. FIS characteristic for (a) the default multi-parametric FIS and (b) the dedicated multi-parametric FIS for the geofence.

3.2.3 Optimization of dynamic spatial offsets

3.2.3.1 Construction of spatial references

Within the sensor-tractor-spreader system introduced in section 3.2.1, various spatial offsets need to be considered to enhance the accuracy of DR determination and realization within the field. Beyond the FISs, a further main subsystem of the real-time control was responsible for dynamic modeling and compensation of these lags. As a fundamental prerequisite, relevant spatial references were identified. In Figure 3.4, they are illustrated schematically for the examined system. In the whole process from the DR determination for specific georeferenced positions to the realization in the spread pattern, a subdivision into two sections left and right of the forward direction within the working width w of 24 m was followed. The definition of these sections was based on results from static spreading tests with a single disc that were conducted by the spreader manufacturer using the same fertilizer as used on the experimental field and applying different settings in terms of the fertilizer drop point, disc speed and dosing orifice position. These datasets included the mean values of normal distributions fit to the angular and radial fertilizer distribution (μ_a and μ_r, respectively) relative to the disc center. These mean values approximately describe the location of the focal points of the pattern (P_{fl} and P_{fr}, respectively). A dataset with settings close to the ones applied later in the measurements with the real-time control was chosen and consequently, considering also the spacing s_d between the two discs of the spreader, the measures d_1 and d_2 defining the relative position of P_{fl} and P_{fr} were defined as follows:

$$d_1 = \sin(\mu_a) \times \mu_r + \left(\frac{s_d}{2}\right) \tag{3.1}$$

$$d_2 = \cos(\mu_a) \times \mu_r \tag{3.2}$$

With μ_a and μ_r given with 19° and 15.5 m, respectively, and s_d being determined with 1.1 m, d_1 and d_2 resulted in 5.6 m and 14.7 m, respectively. As a prerequisite for absolute positioning concerning the spread pattern and the sensor, the longitudinal offset between the GNSS antenna and the center of the spreading discs d_3 was determined with 2.1 m, whereas the offset d_4 between the antenna and the middle of the N-Sensor's traverse was defined with 0.5 m.

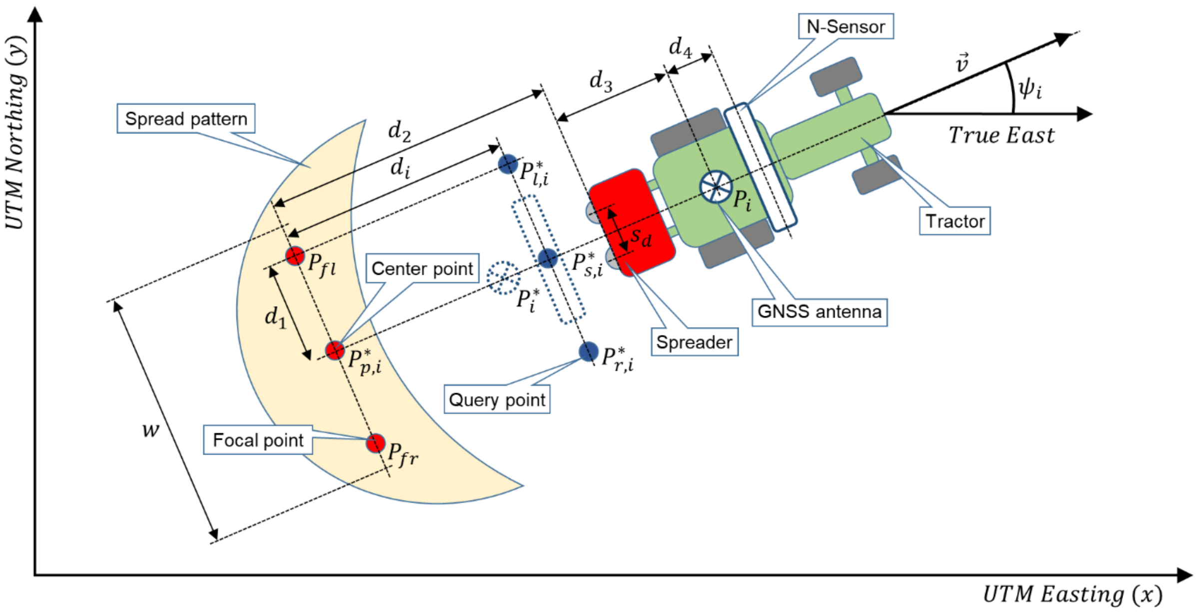

Figure 3.4. Schematic illustration of relevant spatial references within the sensor-tractor-spreader system.

The real-time control continuously received SN and GNSS position data from the N-Sensor software at 1 Hz and 5 Hz, respectively. Each main processing cycle i of the real-time control was initiated by the reception of SN values with a UNIX system timestamp $t_{SN,i}$ in s. The next incoming position data and their timestamp $t_{GNSS,i}$ were then considered for further processing. The geographic coordinates of the antenna given in the WGS84 datum were transformed using the UTM projection in order to have its position $P_i(x_i|y_i)$ in cartesian coordinates. Then, subsequent geometric calculations were performed to construct necessary spatial references. For this, a methodology was followed, which was presented by Heiß et al. (2019). A fundamental basis for the transformations was the calculation of the tractor's heading ψ_i relative to a unit vector pointing eastwards and being parallel to the UTM Easting, whereby the current position, as well as the position at the third processing cycle before, were considered as follows:

$$\psi_i = \begin{cases} \cos^{-1}\left(\frac{\binom{0}{1}\circ\left(\binom{x_i}{y_i}-\binom{x_{i-3}}{y_{i-3}}\right)}{\left|\binom{0}{1}\right|\cdot\left|\left(\binom{x_i}{y_i}-\binom{x_{i-3}}{y_{i-3}}\right)\right|}\right), (y_i - y_{i-3}) \geq 0 \\ 2 \times \pi - \cos^{-1}\left(\frac{\binom{0}{1}\circ\left(\binom{x_i}{y_i}-\binom{x_{i-3}}{y_{i-3}}\right)}{\left|\binom{0}{1}\right|\cdot\left|\left(\binom{x_i}{y_i}-\binom{x_{i-3}}{y_{i-3}}\right)\right|}\right), (y_i - y_{i-3}) < 0 \end{cases} \tag{3.3}$$

The coordinates of all spatial reference points deduced by applying transformations on the initial absolute antenna position P_i are marked hereafter with an asterisk. In general, the calculation of x^* and y^* followed the following formulas:

$$x^* = \cos(\alpha) \times d + x \tag{3.4}$$

$$y^* = \sin(\alpha) \times d + y \tag{3.5}$$

where the corresponding variables α, d, x and y are defined in Table 3.1 for the specific spatial reference points of interest.

Table 3.1. Definitions of variables in Eq. (3.4) and (3.5) for points resulting from transformations of P_i.

Spatial reference point	α	d	x	y
$P_i^*(x_i^*\|y_i^*)$	ψ_{i-1}	$-v_{i-1} \times (t_{GNSS,i-1} - t_{SN,i-1})$	x_{i-1}	y_{i-1}
$P_{l,i}^*\left(x_{l,i}^*\|y_{l,i}^*\right)$	$\psi_{i-1} + \tan^{-1}\left(\frac{d_1}{d_4}\right)$	$\sqrt{(d_1)^2 + (d_4)^2}$	x_i^*	y_i^*
$P_{r,i}^*\left(x_{r,i}^*\|y_{r,i}^*\right)$	$\psi_{i-1} - \tan^{-1}\left(\frac{d_1}{d_4}\right)$	$\sqrt{(d_1)^2 + (d_4)^2}$	x_i^*	y_i^*
$P_{s,i}^*\left(x_{s,i}^*\|y_{s,i}^*\right)$	ψ_{i-1}	d_4	x_i^*	y_i^*
$P_{p,i}^*\left(x_{p,i}^*\|y_{p,i}^*\right)$	ψ_i	$d_2 + d_3$	x_i	y_i

Due to the internal measurement cycles of the N-Sensor system, the incoming SN data had a latency and had to be assigned to a location of 1 s before. Thus, within a main processing cycle i, first of all, the SN and GNSS data corresponding to timestamps $t_{SN,i-1}$ and $t_{GNSS,i-1}$, respectively, were considered. P_{i-1} was used directly to estimate the absolute position $P_i^*(x_i^*|y_i^*)$ of the antenna at the timestamp that was assigned to the SN data being processed. As the streams of SN and GNSS position data were not concurrent, there was a varying span between $t_{SN,i-1}$ and $t_{GNSS,i-1}$, which had a theoretical maximum of 200 ms due to the streaming frequencies. Thus, the wheel-based machine speed v in m s^{-1}, deduced from wheel-based speed and distance (WBSD) messages as specified in ISO (2009a), was considered to compensate this offset and calculate the coordinates of P_i^*. Based on that, the absolute positions $P_{l,i}^*\left(x_{l,i}^*|y_{l,i}^*\right)$ and $P_{r,i}^*\left(x_{r,i}^*|y_{r,i}^*\right)$ of the left and right query point, as well as the center point $P_{s,i}^*\left(x_{s,i}^*|y_{s,i}^*\right)$ in the middle of them were calculated. $P_{l,i}^*$ and $P_{r,i}^*$ defined specific locations, where map-based ECa information was requested, and DR values for the left and right section were determined by the FISs. The DRs were subsequently settled to the N-content of the fertilizer, thus being expressed as SRs of kg ha^{-1} of fertilizer for the left and right section. $P_{s,i}^*$ was on the one hand needed to request interpolated SN data during the verification experiments of the real-time control. On the other hand, it was one parameter needed to define the dynamic offset d_i. The second parameter needed for this was the absolute position of the spread pattern's center point $P_{p,i}^*\left(x_{p,i}^*|y_{p,i}^*\right)$. To define this spatial reference point, again a transformation was conducted using Eq. (3.4) and (3.5) with the values indicated in Table 3.1. The starting point in this case was P_i because the most recent GNSS position was used to estimate the current absolute position of the spread pattern. Finally, d_i in m was calculated as follows:

$$d_i = \sqrt{\left(x_{s,i}^* - x_{p,i}^*\right)^2 + \left(y_{s,i}^* - y_{p,i}^*\right)^2} \tag{3.6}$$

3.2.3.2 Dynamic optimization model

The dynamic offset d_i varied depending on v_i, v_{i-1} and the asynchronous stream of SN and GNSS position data. An optimization model was applied to define the time delay needed for sending the SRs to the spreader in order to accomplish the switching at the match of query points and the spread pattern's focal points. To estimate this match in the spatial domain, the wheel-based machine distance D as specified in ISO (2009a) was used, which corresponds to the covered distance of the tractor in m. The dynamic offset d_i was added to D_i at each main processing cycle i of the real-time control to define the target value $D_{e,i}$. As soon as the tractor was moving, a dedicated timer for the left and right section was created at cycle i. Each timer function contained information about the section, the $D_{e,i}$ and the corresponding SR. The timers were used to trigger the transmission of SRs for each section in the near future and they were deleted afterwards. The starting time of each existing timer j was updated within each cycle i based on the estimated remaining time to reach $D_{e,j}$, as well as further corrections that were needed to compensate temporal lags within the spreader system. Those were the time for the actuators to change the SR (t_a), as well as the time for the fertilizer to drop on the spreading discs (t_f). For t_f, a free fall was assumed and consequently, the calculation was as follows:

$$t_f = \sqrt{\frac{2 \times h}{g}} \tag{3.7}$$

where h corresponds to the height of fertilizer fall, which was determined with 0.14 m, and g corresponds to the acceleration of gravity given with 9.81 m s^{-2}. Thus, t_f was calculated as a constant with 0.17 s.

In terms of t_a, a dynamic calculation was performed for the timer j being updated, based on the expected mass flow changes from one SR change to the next. With information provided by the spreader manufacturer, a lookup table could be deposited in the real-time control, which characterized the relationship between dosing orifice opening angle and mass flow q given in kg min^{-1}. Within the update cycle of the timers, the mass flow change Δq_j was estimated for timer j. For this, the following formula was used:

$$\Delta q_j = \left| w \times 0.006 \times v_i \times (r_t - r_{s,j}) \right| \tag{3.8}$$

where w corresponds to the working width of 24 m, $r_{s,j}$ corresponds to the SR deposited in timer j and r_t corresponds to the last SR for the left or right section, respectively, which had been transmitted from the real-time control to the spreader. Based on Δq_j, the dosing orifice opening angle was estimated by applying a linear interpolation on the values in the lookup table. Assuming a constant traversing speed given by the manufacturer, the traversing time $t_{a,j}$ in s was defined. Then, the delay time $t_{d,j}$ in s of the timer j being updated was recalculated, whereby the calculation was as follows:

$$t_{d,j} = \frac{(D_{e,j} - D_i)}{v_i} + t_f + t_{a,j} \tag{3.9}$$

3.2.4 Real-time control

3.2.4.1 Implementation

The real-time control was implemented on the controller platform by developing dedicated software in MATLAB, whereby the FISs described in section 3.2.2, as well as the geofence, the ECa and historic SN data presented in Figure 3.2b were deposited. Then, the control was embedded into the existing sensor-tractor-spreader system presented in section 3.2.1. The reception of SN and GNSS data from the N-Sensor software was established with a TCP/IP port, whereas the communication with the ISOBUS was realized via a CAN channel. The latter was provided by a VN1610 CAN interface (Vector Informatik GmbH, Stuttgart, Germany), which was linked to the ISOBUS with a branch between the in-cab plug and the terminal. A dedicated function of the real-time control was responsible for receiving and parsing the wheel-based speed and distance messages as defined in ISO (2009a), which were transmitted by the tractor ECU at 10 Hz. They contained information about the parameters v and D, which were provided globally within the real-time control. In Figure 3.5, its basic working principle is illustrated schematically for a main processing cycle i. In general, relevant parameters were timestamped and saved in a log file for being able to provide them in subsequent cycles and for later analysis purposes.

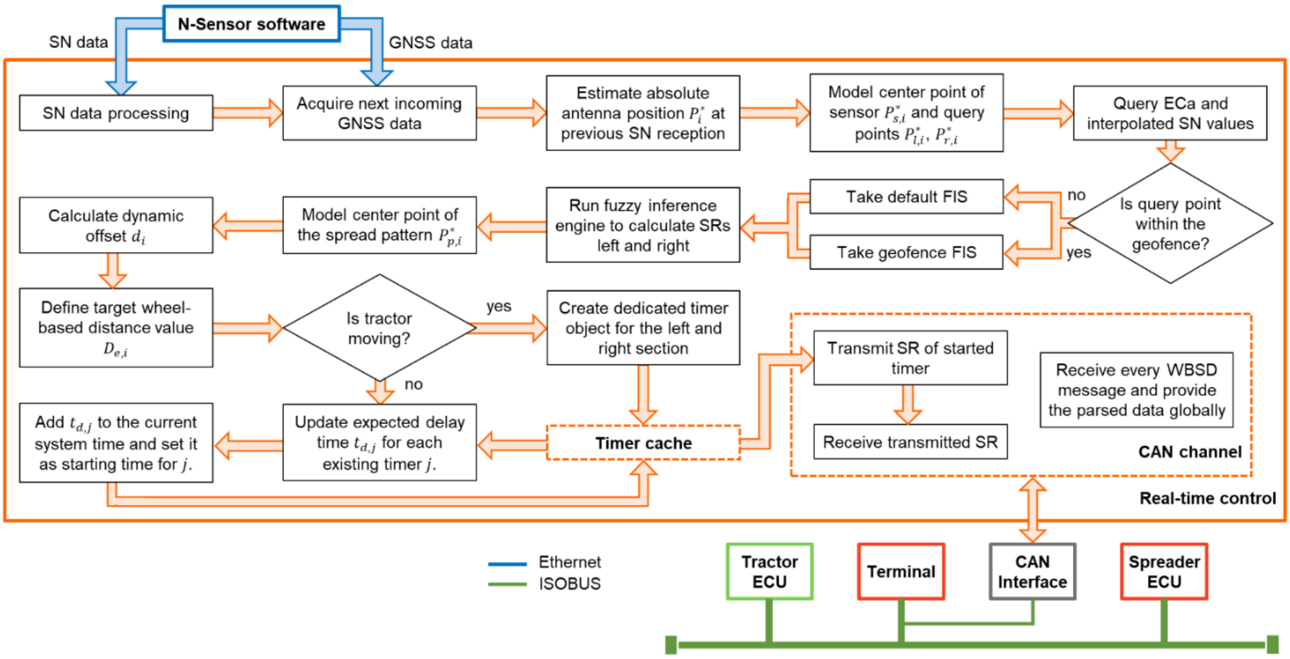

Figure 3.5. Schematic illustration of the real-time control's working principle.

After switching the N-Sensor software to the operation mode, it was continuously streaming SN and GNSS position data via the TCP/IP port. Cycle i was initiated after two dedicated SN values for the left and right sensor head had been sent. As outlined in section 3.2.3.1, transformations were conducted to define various spatial reference points. At each query point $P_{l,i}^*$ and $P_{r,i}^*$, a dedicated ECa value was requested from the deposited map. From the SN point data, a single value was queried at $P_{s,i}^*$ using MATLAB's *scatteredInterpolant* function. The reason for this was that also in a real application, only a mean SN value from both sensing heads would be used to eliminate potential error sources like e.g. the phototropic behavior of the crop, which could influence the canopy structure (Major et al., 2003; Vanderbilt et al., 1981). For $P_{l,i}^*$ and $P_{r,i}^*$, respectively, the real-time control checked separately, if the point was within the geofence and subsequently used the corresponding FIS to define first the DRs and settle them to SRs.

With $D_{e,i}$, the absolute spatial offset between DR definition and application for cycle i was described. Depending on the condition that the current wheel-based speed v_i was greater than zero, a dedicated timer object was created and stored in a timer cache. If v_i was zero, the real-time control directly passed to update the starting time of each timer j within the cache based on the current system time and the delay time $t_{d,j}$. When the tractor was accelerating, it was likely to happen that the starting time of a timer was already in the past. In this case, it was configured to be started as soon as possible. The timers were started independently from the main processing cycles, as soon as the controller platform's system time matched with their respective starting time and subsequently, the transmission of the deposited SR to the ISOBUS was triggered. Hereby, the SR value was considered as a data dictionary entity 6 according to VDMA (2021), which corresponds to the setpoint mass per area application rate. Subsequently, the information was packed into a process data message predefined according to ISO (2009b), whereby there were two different messages for the left and right section, respectively. This message was then sent on the ISOBUS via the CAN channel to be read by the spreader ECU. To verify its transmission and evaluate the performance of the real-time control in a post-processing analysis, it was immediately received again as soon as it appeared on the ISOBUS.

3.2.4.2 Evaluation

In order to verify its functionality and define its limitations, measurements with the real-time control were conducted on tracks A and B indicated in Figure 3.2. They were chosen because preceding simulations with the FISs and the available input data indicated comparatively high SR variations to be expected along the tracks. Track A was always driven on from West to East, whereas it was the opposite direction for track B. For the measurements with the real-time control, six different variants in terms of the driving speed of the tractor were followed in two repetitions conducted on each track. Four variants were performed with the cruise control of the tractor set to a constant speed of 6, 12, 16 and 20 km h^{-1}. The speeds of 6 and 20 km h^{-1} were chosen because they were the lowest and highest values, respectively, for which settings were given in the spreading table provided by the manufacturer. The choice of 12 km h^{-1} represented a very common speed that also all descriptions in the spreader's owner manual were based on, whereas 16 km h^{-1} could be considered as a high operating speed that is still quite common among farmers. A further variant (S) was conducted with a constant speed of 12 km h^{-1}, whereby the tractor was stopped two times within the track and reaccelerated to the constant speed after waiting at least 10 seconds. For the last variant (V), the tractor was continuously accelerated from 0 km h^{-1} at the beginning of a track up to approx. 20 km h^{-1} at the middle of the track, from where it was deaccelerated back to 0 km h^{-1} until the end of the track. Considering all different measurement setups, 24 datasets were recorded in total. After recording a dataset, the MATLAB script executing the real-time control was stopped and restarted at the beginning of a new record. Before each of the two repetitions, the tractor, spreader, terminal, as well as controller platform were shut down and restarted. The N-Sensor system was switched to the operating mode at the beginning of each repetition and remained in this mode for its whole duration.

For further analyses on the recorded datasets, they were subdivided based on the two sections left and right. The designation of the datasets is following this. Every dataset is indicated with an A or a B for the two tracks and indexed successively with indicators for the speed variant (6, 12, 16, 20, S and V), the section left and right (L and R, respectively), as well as the number of the repetition. So, dataset $A_{V,L,2}$ for instance corresponds to the record for the left section, conducted within the second repetition on track A with the variable speed variant. To consider only the usual operating status of the system, the record for processing cycle i was only considered if both of its timers were actually started and the corresponding SRs were sent on the ISOBUS. Furthermore, all recordings with a v_i of less than 1 m s^{-1} were excluded. A very important parameter for the evaluation of the real-time control's performance was the deviation ε expressed as a spatial offset in m between the query points and the corresponding focal points, which should be ideally 0 m. It was estimated as follows for each started timer k that had been created in processing cycle i:

$$\varepsilon_k = D_{e,i} - D_k - t_{d,k} \times v_k \tag{3.10}$$

where $D_{e,i}$ corresponds to the target wheel-based distance value defined in i and D_k corresponds to the wheel-based distance value at the UNIX system timestamp t_k, when the SR deposited in k had been received again from the ISOBUS. This parameter was determined by applying a linear interpolation at t_k on all timestamped D values recorded from the ISOBUS. Parameter $t_{d,k}$ corresponds to the delay time that had been defined for k in its last update before being started, whereas v_k corresponds to the current wheel-based speed value at this update. The delay time $t_{d,k}$ was neglected in Eq. 3.10 in case the affected timer had to be sent immediately due to an obsolete starting time.

3.3 Results and discussion

3.3.1 Output generated by the fuzzy inference systems

Within the real-time control, the inference engine processed the input data acquired from the query points based on the defined FIS characteristics. The system checked for each query point separately if it was within the geofence, used the corresponding FIS and calculated the SR. In Figure 3.6, the outputted SRs from the left and right section are plotted for each recording of exemplary edited datasets. As the tracks were almost exactly running along the east-west axis, the UTM Easting is indicated on the x-axis. Datasets from the 6 km h^{-1} variant were chosen because they have the highest resolution of SR recordings. It is apparent from Figure 3.6a that around the edges of the geofence, there were comparatively high differences between the left and right section, which is indicated with the shaded areas between the graphs. Here, the query point of one section of the application system was within the geofence, whereas the other one was not. Within the geofence, the SRs for the left and right section were identical, which is explained by the fact that the geofence FIS did not allow a SR variation depending on the ECa and used only the mean SN value. It can be seen that outside the geofence, the SRs from the two sections were largely close to each other along track A. Only in a few cases, the difference reached 10 kg ha^{-1} or more. A similar pattern can be observed in Figure 3.6b, where the results from exemplary datasets recorded on track B are presented. With 5.6 m, d_1 was close to an even lateral sampling distance, which would have been reached at 6 m considering the tramline width of 24 m. So, the reason for the largely small deviations between the left and right SRs is to be found in the fact that the SR distinction was only based on the input ECa and that this parameter most probably did not have big changes between the left and right query points. This assumption is supported by the fact that for soil parameters, lower heterogeneities can be expected than for the crop biomass (Griepentrog et al., 2007).

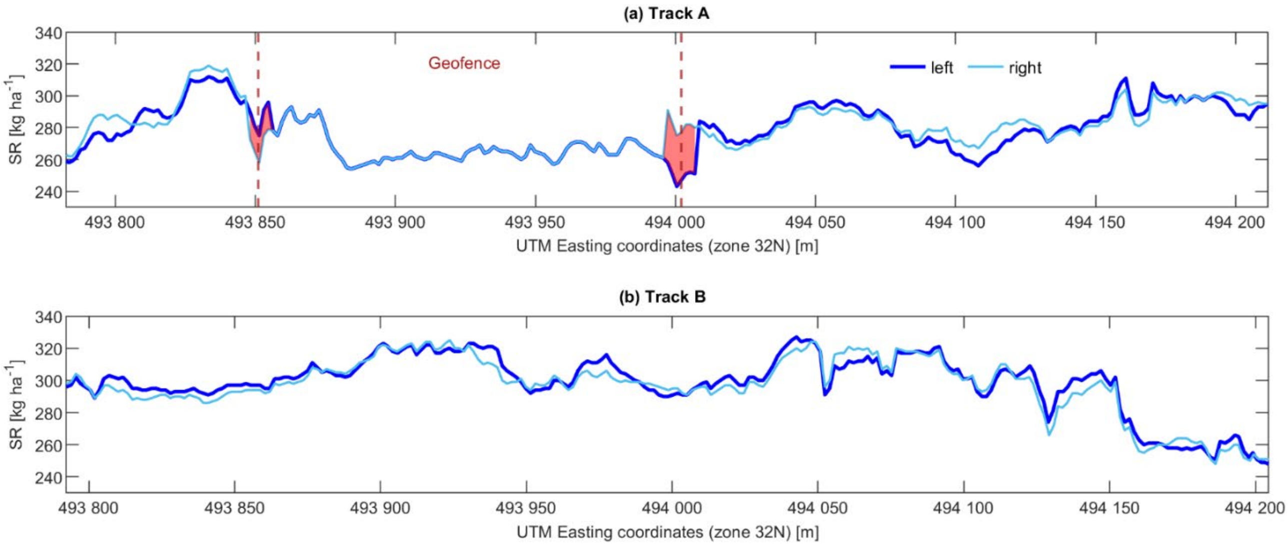

Figure 3.6. Recorded left and right SR values. (a) datasets $A_{6,L,1}$ and $A_{6,R,1}$ and (b) datasets $B_{6,L,1}$ and $B_{6,R,1}$

3.3.2 Real-time control evaluation

As outlined in sections 3.2.4.1 and 3.2.4.2, the SR deposited in each started timer object was received again from the real-time control, as soon as it had been sent on the ISOBUS. An analysis of all edited datasets resulted that, except for the first recordings in datasets $A_{12,L,2}$ and $A_{12,R,2}$, each SR defined for a query point was successfully transmitted and there was none skipped. Further analyses have shown that for both exceptions, the functions for transmitting the SRs were called, however. So, the SRs were most probably transmitted but their transmission could not be verified. For the timers assigned to these recordings and their respective preceding ones, there was a difference of only 9 ms in terms of their planned starting time. So, the most reasonable explanation for this missing proof of

SR transmission is that the function being responsible for receiving and parsing the process data messages skipped the affected ones.

The main parameter to quantitatively describe the performance of the real-time control in the spatial domain was the deviation ε. In Figure 3.7, the results are shown for exemplary datasets from the different constant speed variants. On each subplot, ε in m is plotted against the index i of the main processing cycles from the original, unedited dataset. It is evident from the overall pattern on all subplots that the error behavior has a stochastic nature. In most cases, the value for ε is negative, thus indicating that the corresponding SRs were sent too late. The subplots imply that the offset from the optimum value of 0 m tends to increase with the speed. In terms of the scattering of the results, there is a conspicuous increase from 6 km h^{-1} to 12 km h^{-1}. Beyond that, there seem to be no systematic changes from the 12 km h^{-1} to the 16 km h^{-1} and 20 km h^{-1} variants, respectively.

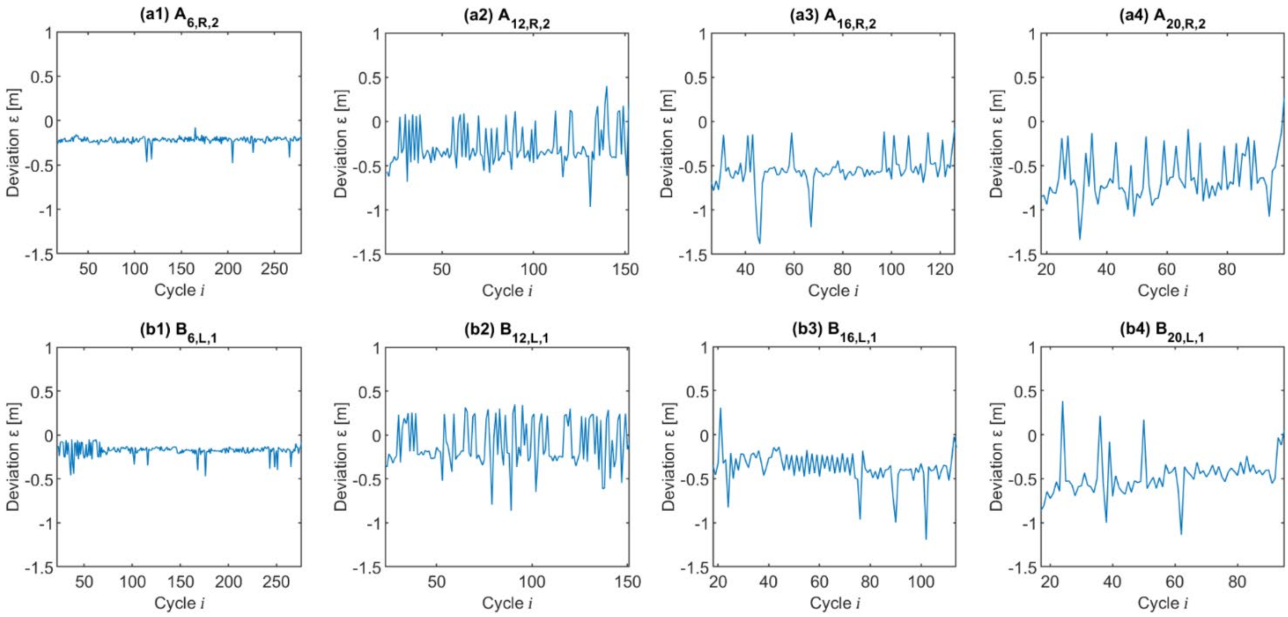

Figure 3.7. Deviation ε at different constant speeds. (a1)-(a4) showing datasets for the right section, repetition two and track A, (b1)-(b4) showing datasets for the left section, repetition one and track B.

To assess the real-time control's behavior at interruptions, a variant with a constant speed of 12 km h^{-1} and two intermediate stops was conducted. In Figure 3.8, the results in terms of the deviation ε are presented for two exemplary datasets. The processing cycles where the tractor was stopped are indicated and since the cyclic SR calculation was paused by the algorithm, a straight line is drawn from the last cycle before and the first cycle after a stop, respectively. Both subplots of Figure 3.8 indicate a slight tendency that the scattering is smaller at the first few cycles after a stop. Apart from that, no saliencies can be observed for the course of ε before and after a stop.

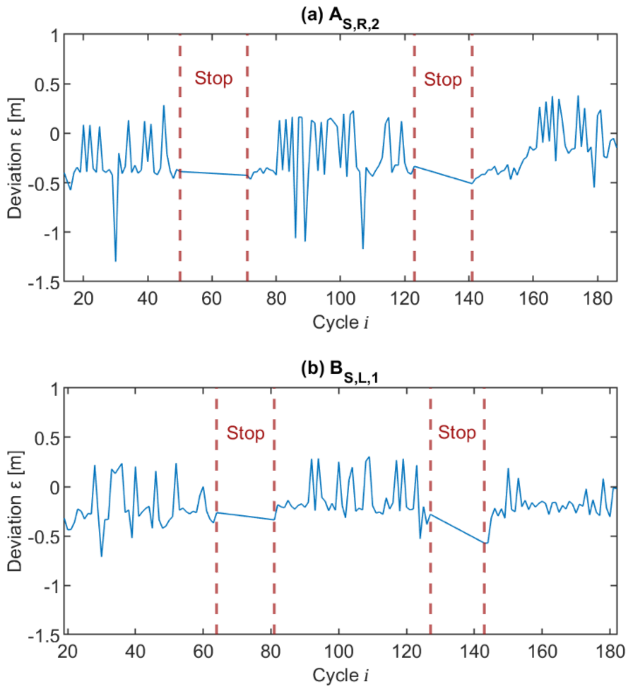

Figure 3.8. Deviation ε for a constant speed of 12 km h^{-1} and intermediate stops. (a) showing exemplary dataset for the right section, repetition two and track A and (b) showing exemplary dataset for the left section, repetition one and track B.

The results presented in Figure 3.7 already imply a dependency between the tractor speed and the deviation ε. In Figure 3.9, the results in terms of the deviation ε are shown for exemplary datasets from the variable speed variant. Also, the wheel-based speed v_k from the last update of the corresponding timer is plotted. Comparing all subplots, ε apparently increases with the speed in terms of the offset, as well as the scattering. This could be traced back to inherent latencies in the processed data streams, as well as their limited temporal resolutions, which has a higher influence on deviation ε as the speed increases. Further, it seems that the scattering is increased in repetition two compared to repetition one and there seem to be positive peaks of deviation ε when the speed v_k is close to the maximum of 20 km h^{-1}. Both observations, however, could not be traced back to a specific cause but are rather related to the stochastic character of the error behavior.

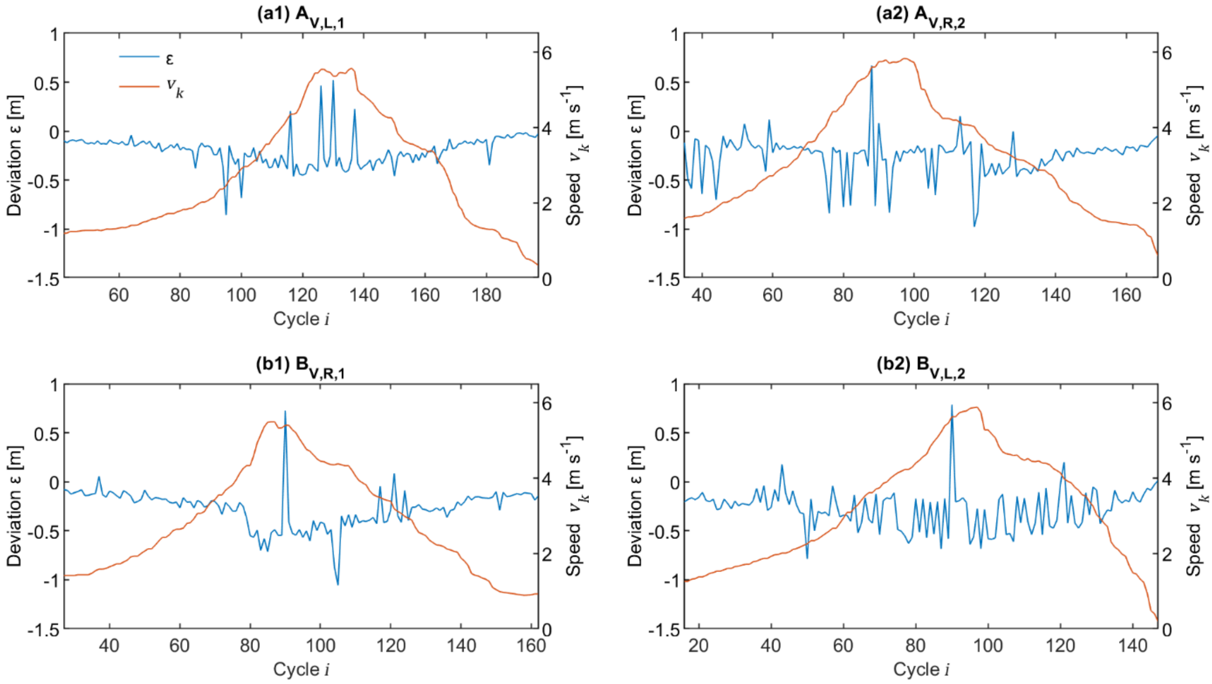

Figure 3.9. Deviation ε for the variable speed variant. (a1)-(a2) showing exemplary datasets for track A, (b1)-(b2) showing exemplary datasets for track B.

MATLAB's *boxplot* function was used to graphically illustrate the distribution of the deviation ε within each dataset. The corresponding results for the constant speed variants are shown in Figure 3.10. The red mark within each box indicates the median and the bottom and top edges indicate the 25^{th} and 75^{th} percentiles, respectively. The whiskers extend to the most extreme data points not considered as outliers, whereas the outliers themselves are illustrated with a red cross. Outliers are all values that are more than 1.5 times the interquartile range away from the bottom or top of the blue box. A visual analysis of repetition one and two within each subplot of Figure 3.10 suggests that there is no systematic difference in terms of the error behavior. Comparing the datasets for the left and right section, respectively, from the same original records implies that there are only slight differences in terms of the distribution of the data values. An exception can be found with datasets $A_{12,L,2}$ and $A_{12,R,2}$. Further analyses did not suggest that there is a correlation to the fact that these were the two datasets, where the first SR transmission could not be verified. Also, they did not allow for any other conclusions on possible explanations.

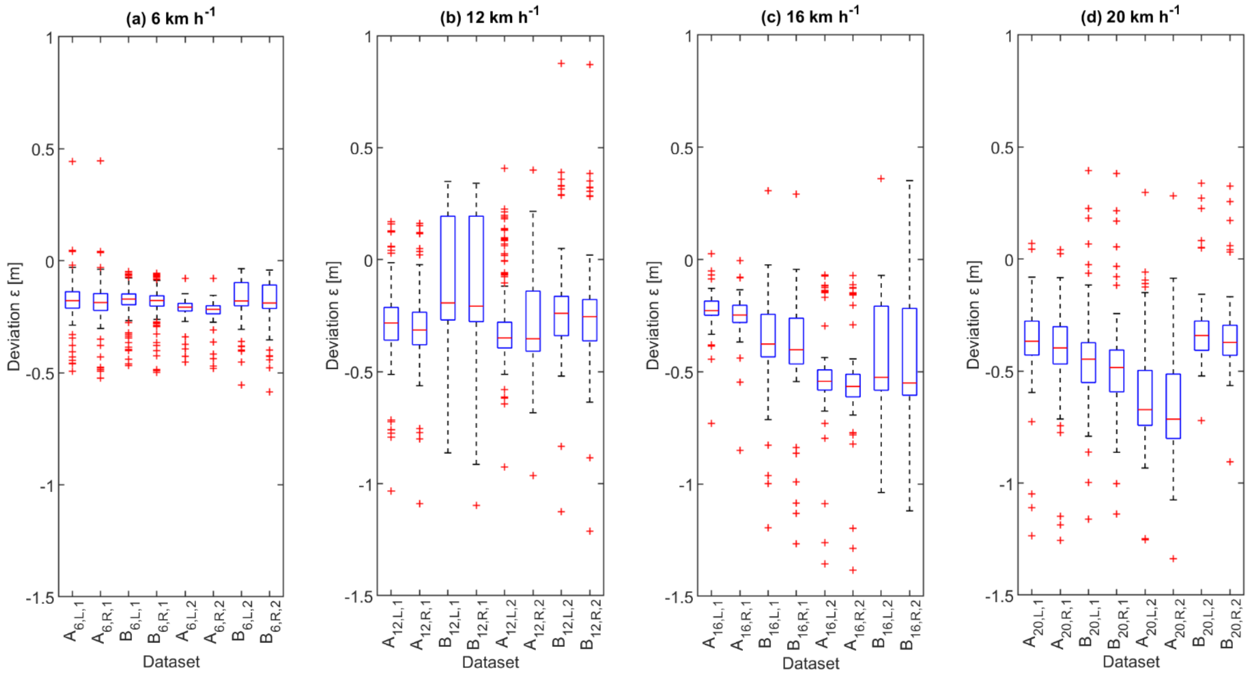

Figure 3.10. Box plots for all datasets from the (a) 6 km h^{-1}, (b) 12 km h^{-1}, (c) 16 km h^{-1} and (d) 20 km h^{-1} variant.

In general, the box plots presented in Figure 3.10 confirm once more that random effects are inherent to the real-time control's error behavior and that their influence tends to increase with the speed. The most obvious explanations for this are limited resolutions and asynchronies of the different data streams, as well as the software setup of the controller platform, which is basically not designed for handling hard real-time constraints. The complexity of different tasks being scheduled and executed by the operating system in the background makes it difficult to identify error sources that appear in specific circumstances. However, the absolute deviation is largely below 1 m and never exceeds a range of -1.5 m to 1 m, even within the 20 km h^{-1} variant, which can be considered as an exceptionally high speed. The percentage of recordings with an absolute deviation ε of more than 1 m is 0, 0.48, 1.5 and 2.3% for the different constant speed variants with 6, 12, 16 and 20 km h^{-1}. The highest ε was found with -1.34 m in dataset $A_{16,R,2}$. From a practical perspective, the magnitude of these deviations can be considered negligible because there are various other technical restrictions that are likely to cause more error. For instance, the limitations of the dosing and metering system within the spreader have an effect on the adequate realization of SRs within the field. Also, varying ballistic properties of the fertilizer granules or external error sources like e.g. the wind or the unevenness of the soil along the tramline could have more significant effects on the quality of the fertilizer distribution. Finally, unlike e.g. pneumatic spreaders or sprayers, centrifugal spreaders have the unique characteristic of distributing the fertilizer over a crescent plane, whose longitudinal extent is usually much larger than the travelled distance between the single SR commands given by a real-time sensor system. This will always result in average values of applied fertilizer instead of a distinct realization of the SR commands.

In Figure 3.11, the boxplots for the further two speed variants are presented, whereby in Figure 3.11a, the datasets from the variant with 12 km h^{-1} and intermediate stops, and in Figure 3.11b, the datasets from the variable speed variant are shown. When comparing both subplots, a difference between the repetitions is implied in Figure 3.11a and a slight difference between the tracks is suggested in Figure 3.11b. Once more, no systematic reason could be identified for this but rather the influence of random effects has to be assumed. Both speed variants represent a test of the real-time control beyond its envisaged operating conditions in terms of the driving speed. Still, the deviation ε exceeded an absolute value of 1 m in only 0.12% of the cases for the variant with 12 km h^{-1} and intermediate stops, while this value was with 0.09% even lower in the variable speed variant.

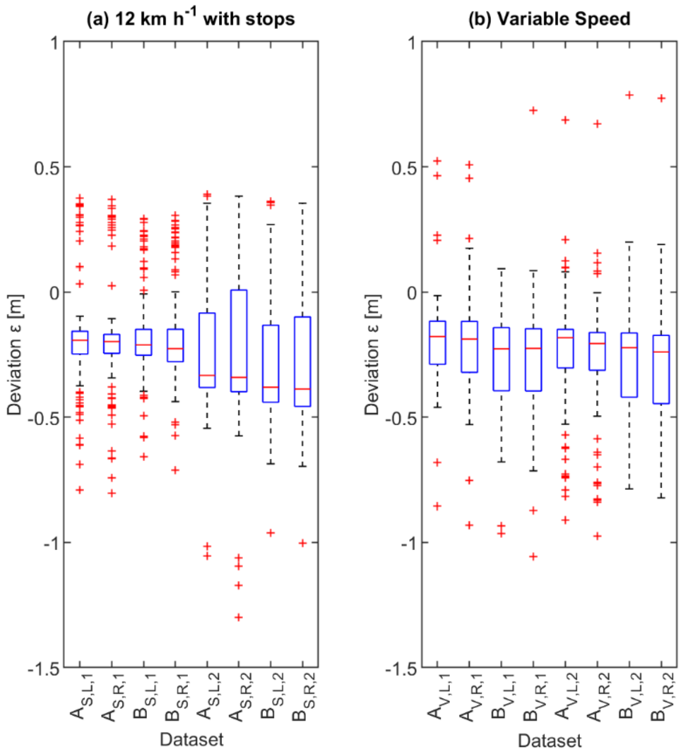

Figure 3.11. Box plots for all datasets from (a) the variant with 12 km h^{-1} and intermediate stops and (b) the variable speed variant.

3.4 Conclusion

Two FISs for fusing the Yara N-Sensor ALS2 system's agronomic algorithms with soil ECa data based on expert knowledge were incorporated into a real-time control to generate SR commands for two dedicated sections within a centrifugal spreader on-the-go. Measurements with SN and ECa data from the real application have shown that the SR difference for the left and right section rarely exceeded 10 kg ha^{-1} because it was only based on dedicated ECa values. An algorithm, which scheduled the transmission of SR commands by periodically predicting the spatial concordance of DR determiniation and application with an odometric approach, was implemented as a further main component of the real-time control. In a verification with different speed variants covering also borderline conditions, the system has shown a high consistency. Even if the error behavior of the dynamic offset optimization had a highly stochastic character, the absolute deviation never exceeded 1.5 m and deviations beyond 1 m ranged from 0.09 to 2.3% among the different recorded datasets, which can be considered sufficient for practical needs. The dynamic optimization of inherent spatial offsets and technical temporal lags offers the opportunity to increase the precision of the application and include the driving speed as a further control parameter.

Due to the generic nature of the approach, it can be extended with further quantifiable latencies and even transferred to other applicators like e.g. pneumatic spreaders or sprayers, where the effect on the application accuracy is presumably higher due to the more distinct SR realization on the field. Also, a transfer of the methodology to prescription map based VRNA is basically possible. Future work could deal with analysing the impact of the offset optimization on the actually applied amounts on the field using simulations involving granule trajectory modeling, as conducted by Sharipov et al. (2021). To support the expert's decision making process and automate the whole process of multi-parametric real-time VRNA, suitable user interfaces and infrastructures for eased data handling should be developed.

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CHAPTER 4

Paper C

Versatile and user-centered concept for temporally and spatially adapted nitrogen application based on multiple parameters[3]

Andreas Heiß, Dimitrios S. Paraforos, Galibjon M. Sharipov, Peter Ullrich, Julian Bruns, Andreas Abecker and Hans W. Griepentrog

Abstract

Crop nitrogen (N) demand is defined by various physiological, management and environmental factors that interact with each other and involve temporal and spatial dynamics. Variable rate N application (VRNA) intends to address this but the underlying algorithms often remain rather rigid and deterministic, are partly subject to high uncertainties and largely leave the agronomic expert's knowledge and experience unnoticed.

A novel generic system architecture was conceptualized to overcome these limitations and respond to the complexity of N management in a straightforward and both, reactive and proactive manner. Having a fuzzy expert system as methodical core, the approach mainly relies on human input to grasp the circumstances at a specific N application and address the required parameter interactions. As a holistic concept, it further aims at a high versatility in terms of considered input data and utilization with different sensor and application technology, as well as a digitized VRNA process chain involving graphical user interfaces to simplify procedures for data presentation, decision making, application and documentation.

Bringing the presented concept into a prototypic implementation considering real-time crop N sensor and mapped soil data, its consistency was verified. At the same time, potential functionalities,

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as well as limitations were illustrated and technical requirements on specific subsystems were clarified by the prototype. The possible risks that stand in the way of high benefits due to a strong focus on expert knowledge can be countered by using digital tools and heading towards hybridization with other VRNA approaches.

Keywords: multi-parametric data fusion, fuzzy expert systems, site-specific N management, multi-source data, graphical user interfaces

4.1 Introduction

To improve synchrony between crop nitrogen (N) supply and demand, thus increasing N recovery, site-specific treatment with variable rate N application (VRNA) is a possible solution (Weckesser et al., 2021; Argento et al., 2020). Its most crucial and still critical aspects nowadays refer to the parameters to be considered, as well as the agronomic algorithms defining the N dose rates (DR). A popular and economical principle is based on delineating management zones of similar productivity potential and subsequent treatment via prescription maps, whereby clustering techniques can be used to merge geodata referring to landscape and soil attributes, historical yield or the crop's N status derived from spectral airborne or satellite data (Li et al., 2007; Morari et al., 2021; Schenatto et al., 2017). A major constraint here is the lack of functional explanations for the existence of different zones, as well as the limited adaption to weather-mediated variability (Heege, 2013a).

Algorithms considering current crop information, which is a key VRNA parameter especially in real-time sensor systems, are abundantly based on rather deterministic N redistribution (Weckesser et al., 2021), while more sophisticated approaches consider the crop's N response (Holland and Schepers, 2010) or aim at an N mass balance (Raun et al., 2005). A combination with management zones in map-overlay is considerable (Paraforos et al., 2019). However, spatially varying crop and further biological, edaphic and topographic factors, as well as their interaction with the weather and management are causing in-season and year-to-year temporal and spatial dynamics affecting N delivery from the soil, crop growth and N response, as well as yield formation and its relation to N inputs (Griepentrog et al., 2007; Scudiero et al., 2018; Colaço and Bramley, 2018; Arnall et al., 2013). This complexity can hardly be handled with single-parametric, mechanistic and generalized models (Colaço et al., 2021). Process-based or statistical crop models addressing this natural complexity in N management have advanced within the last decades but are still affected by significant limitations (Morari et al., 2021; Basso and Liu, 2019). Moving window regression and also machine learning methods were applied to capture dynamic and non-linear parameter interrelations (Scudiero et al., 2018; Chlingaryan et al., 2018). Beyond the environmental influences, however, the production target is an important dynamic factor to be considered as well in the VRNA strategy and apart from yield maximization, there are also economic or environmental protection drivers (Ebertseder et al., 2005).

The use of expert knowledge from farmers and agronomic advisors can be helpful in handling these challenges. In their everyday work they need to accommodate natural, technical and economic factors and over many years of experience and further education, they accumulate a body of salient situational knowledge about the cause-effect relationships within their local crop production systems, which is scientifically not accessible (Lundström and Lindblom, 2018; Hoffmann et al., 2007; Oliver et al., 2012). Expert knowledge is considered as an important source of information to analyse and merge various relevant layers of spatial data and define VRNA system models (Leroux et al., 2018). Martínez-Casasnovas et al. (2018) consider its use as an important factor for the adoption of VRNA technologies. Several authors have used it in the delineation of management zones (Fleming et al., 2000; Guerrero et al., 2021) and in a more implicit manner, it found application in the definition of VRNA strategies (Ferrise et al., 2021; Griepentrog and Kyhn, 2000). However, all in all expert knowledge has received sparse attention so far in the design of VRNA systems (Schenatto et al., 2017).

To incorporate it in a systematic manner as a logical core of VRNA, fuzzy systems are predestined as technological basis. They provide effective and straightforward means to consider multiple inputs in automatic control strategies, have a relatively high robustness and fault tolerance as they can handle imprecision and uncertainties in the parameters and can deal with the complexity and non-linearities in their interactions (Sun et al., 2018; Jahangiri et al., 2019). These properties made them find various application in the context of environmental and agricultural systems (Guillaume et al., 2012). Their straightforward adjustability allows a flexible adaption to different conditions and they are very well adapted to human cognition, thus facilitating the semantic integration as a major challenge to incorporate expert knowledge in VRNA (Giusti and Marsili-Libelli, 2015; Wolfert et al., 2017). Fuzzy systems were successfully employed for region-based optimization of N management (Papadopoulos et al., 2011) and VRNA based on plant, soil, topographic as well as weather information (Bouroubi et al., 2011; Tremblay et al., 2010). A methodology to employ a fuzzy expert system to fuse soil apparent electrical conductivity (ECa) with real-time sensor data providing the crop’s N uptake was presented by Heiß et al. (2021).

Zhai et al. (2020) systematically elaborated upcoming challenges and evaluation criteria for agricultural decision support systems (DSS) considering standardized requirements. Graphical user interfaces (GUI) are of significance in in this context and have a special importance, if expert knowledge is supposed to be a core element. GUI design should be user-centered (Lindblom et al., 2017), address simplicity (Rose et al., 2016) and spare the need for any specific technical skills for operation to achieve acceptance among users from the agricultural domain (Weckesser et al., 2021). As implied by the work of Leroux et al. (2018), beyond the data fusion process itself, a consistent fuzzy expert system needs to cover also spatial data visualization and information, as well as decision support. When it is specifically about VRNA, also the application at the field level needs to be considered because a high flexibility due to different available data, as well as sensor and application technologies is required (Shanahan et al., 2008). Further, a high level of automation is needed to minimize the effort and time demand for data handling and facilitate the execution of different sub-processes of VRNA (Colaço and Bramley, 2018).

In the present paper, a holistic framework for VRNA is conceptualized, which comprises the whole process chain from spatial data analysis, decision making, execution on the field and documentation. Main novelties of the concept lie in (1) an explicit focus on the use of expert knowledge from farmers and agronomic advisors to address the complexity of site-specific N management in terms of the relevance of different input parameters, their inherent spatiotemporal dynamics and different target orientations, (2) a high versatility concerning used input data and application approaches involving real-time, as well as prescription map based technology and (3) a user-centered design approach incorporating GUIs and digital tools to ease the VRNA strategy setup and automate process execution. A prototype of the concept, which was built for the specific use case of a fusion of crop N uptake data sensed by a real-time sensor system and mapped soil ECa data, aims at illustrating the underlying process chain, as well as potentials and limitations of the concept's implementation.

4.2 Conceptual system design

4.2.1 Basic system architecture

The conceptualized system architecture is presented in Figure 4.1 at the highest level of abstraction and incorporating all its potential functionalities. It provides several subsystems to support the user, who is the core element covering three crucial aspects of VRNA. As an agronomic expert, the user makes a decision on the VRNA strategy. Beyond that, the user is responsible for the supervision of the entire process chain, as well as the execution on the field. In many cases, it is realistic that these roles are distributed among different people (Welte et al., 2013). For example, it is possible that the farm owner could be supported by an agronomic consultant in the decision making, while the process chain supervision and execution on the field are covered by the owner and further employees, respectively.

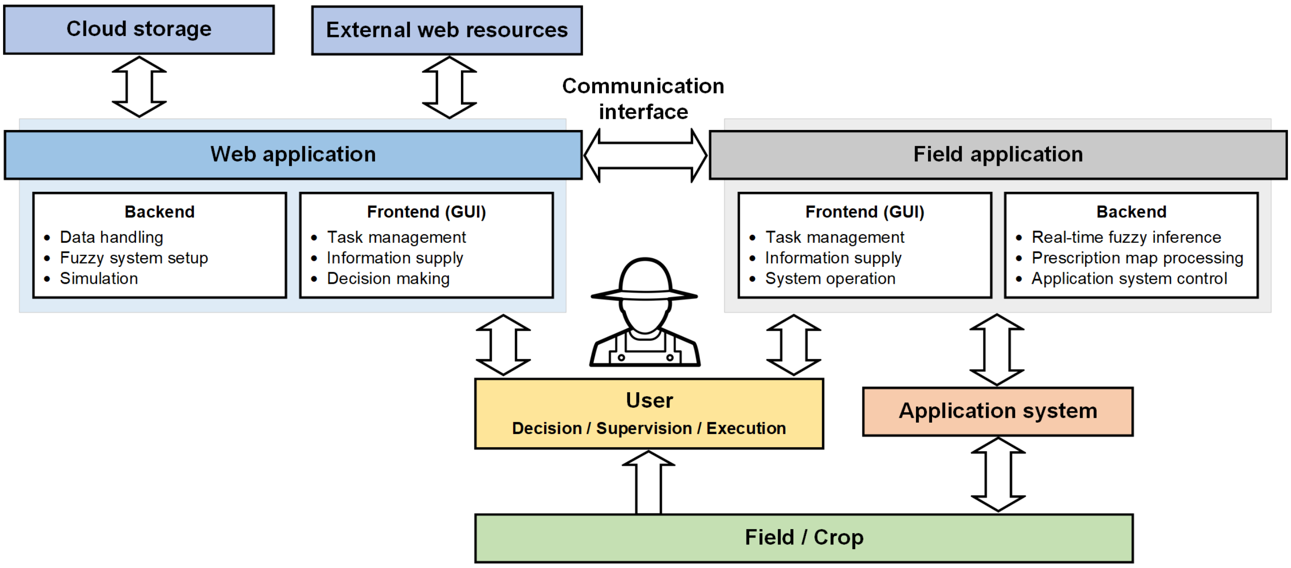

Figure 4.1. Basic system architecture.

A web application is supposed to offer tools for applying the implications of the user's situational field and crop assessment to the definition of a site-specific variation of the DR considering multiple relevant and measurable input parameters. Via a GUI as frontend, the user should be given the opportunity to create and manage specific tasks for each N application. Further, the GUI should provide useful information to refine the analysis in terms of the specific conditions and requirements and thus improve the quality of the decisions (Zhai et al., 2020). This involves mainly the representation of relevant georeferenced input parameters, as well as geodata processed in the web application or returned from the execution of the N application. Further specific requirements on the GUI design can be deduced from the fuzzy expert system presented by Heiß et al. (2021) as this is the core technology used to transfer the agronomic expert's knowledge to a machine readable algorithm fusing multiple parameters. As their number increases, the decision making process is getting more complex and abundantly, there is only a short time window before each N application for defining the VRNA strategy. In front of this background and especially to avoid a frustration of the user, a strong focus needs to be in the GUI design on facilitating the decision making by breaking it down to the most essential aspects and supporting it with suitable elements for decision support (Ferrise et al., 2021; Oliver et al., 2012; Rose et al., 2016). Further, generic algorithms automatically giving adjustable pre-settings could provide partial support.

A further main task of the web application backend is the storage and management of data. Beyond the geodata, this involves the N application tasks created by the user with their associated configurations, as well as some basic data processing routines. Apart from that, the backend is responsible for the setup of the fuzzy system, which is implied in the GUI frontend and is the core of each task configuration. According to Heiß et al. (2021), main aspects for this are the fuzzy classification of input parameter values and the output DR, as well as the setup and weighting of rules linking input and output and implying the characteristic behavior of the system. Finally, the backend should be able to simulate the DR outputs based on the desired input data and the current fuzzy system setup for a specific task. On the one hand, this is a crucial element to give an immediate feedback about the decisions and adapt them iteratively, which is also advocated by Leroux et al. (2018) and reflects the aspect of re-planning as suggested by Zhai et al. (2020). On the other hand, the simulation output can be used directly for generating prescription maps of fertilizer setpoint rates (SR). The core functionalities needed for the simulation are the construction of fuzzy inference systems and a fuzzy inference engine.

The web application is considered as the pivotal point of the architecture because it channels the crucial decision making process concerning the behavior of the multi-parametric VRNA for the subsequent execution on the field. The system architecture is explicitly committed to an internet-based solution offering versatility in the location-independent access with multiple devices, which is important because agronomic decision making can take place partly at the field and the office PC, as well as in interaction between farmers and advisors (Rose et al., 2016). Beyond that, external web resources providing additional agronomically relevant information or further geodata via web map services could be connected to the web application, thus leveraging the system's scalability and interoperability (Zhai et al., 2020). In this context, also the connection to higher-level management systems as presented by Weckesser et al. (2021) or Kempenaar et al. (2021) is conceivable. An important aspect is the digital footprint in terms of accumulated data and required storage. This has to be considered in every case, where mapped information is being involved, and especially when many layers of historic mapped data are used, even if only as a supplementary source of information. As outlined by Kayad et al. (2022), this aspect is lately becoming more and more significant especially with emerging high-resolution remote sensing data and stresses once more the need of relying on cloud-based data management.

For the execution of the VRNA, the system architecture provides a field application that works basically offline but offers the capability of automated, internet-based data exchange with the web application, thus reducing manual input. For this, a communication interface is provided that transfers configurations for scheduled N application tasks, as well as necessary geodata and prescription maps, respectively, from the web to the field application. Analogously, georeferenced process data should be sent back to the web application for documentation purposes or the use in future N applications. The field application should have a GUI in the frontend to allow the user to choose the task to be executed for a specific field and provide some basic task information, as well as possibilities to adjust the configuration, if needed. Further, the GUI should present relevant geodata and process data and allow the user to control and supervise the application process.

To implement the strategy defined in the web application, the field application's backend interacts with the application system, which consists in its core of a fertilizer applicator and, if applicable, a real-time sensor system. For an application including real-time sensor data, the backend needs to be capable of constructing a fuzzy inference system based on the configuration associated to the chosen task. With control algorithms and interfaces as presented by Heiß et al. (2022), real-time sensor system data could be fused with mapped data in a fuzzy inference engine to generate SR commands for the applicator on-the-go. Alternatively, the field application should allow the processing of prescription maps of SRs as it is state of the art for common variable rate application terminals.

4.2.2 Different application approaches

With a multi-parametric fuzzy expert system as presented by Heiß et al. (2021) as a fundamental starting point, the conceptualization of the system architecture described in section 4.2.1 aimed at generic and flexible capabilities in terms of both, the definition of the VRNA strategy, as well as the used sensor and application technology and considered input data. This is of high significance because different farms applying precision agriculture practices employ an enormous variability of sensors and mapped data being associated with different informative properties and cost. In Figure 4.2, the necessary process steps, as well as involved data for all scenarios considered as realistic are systematized according to three different main approaches.

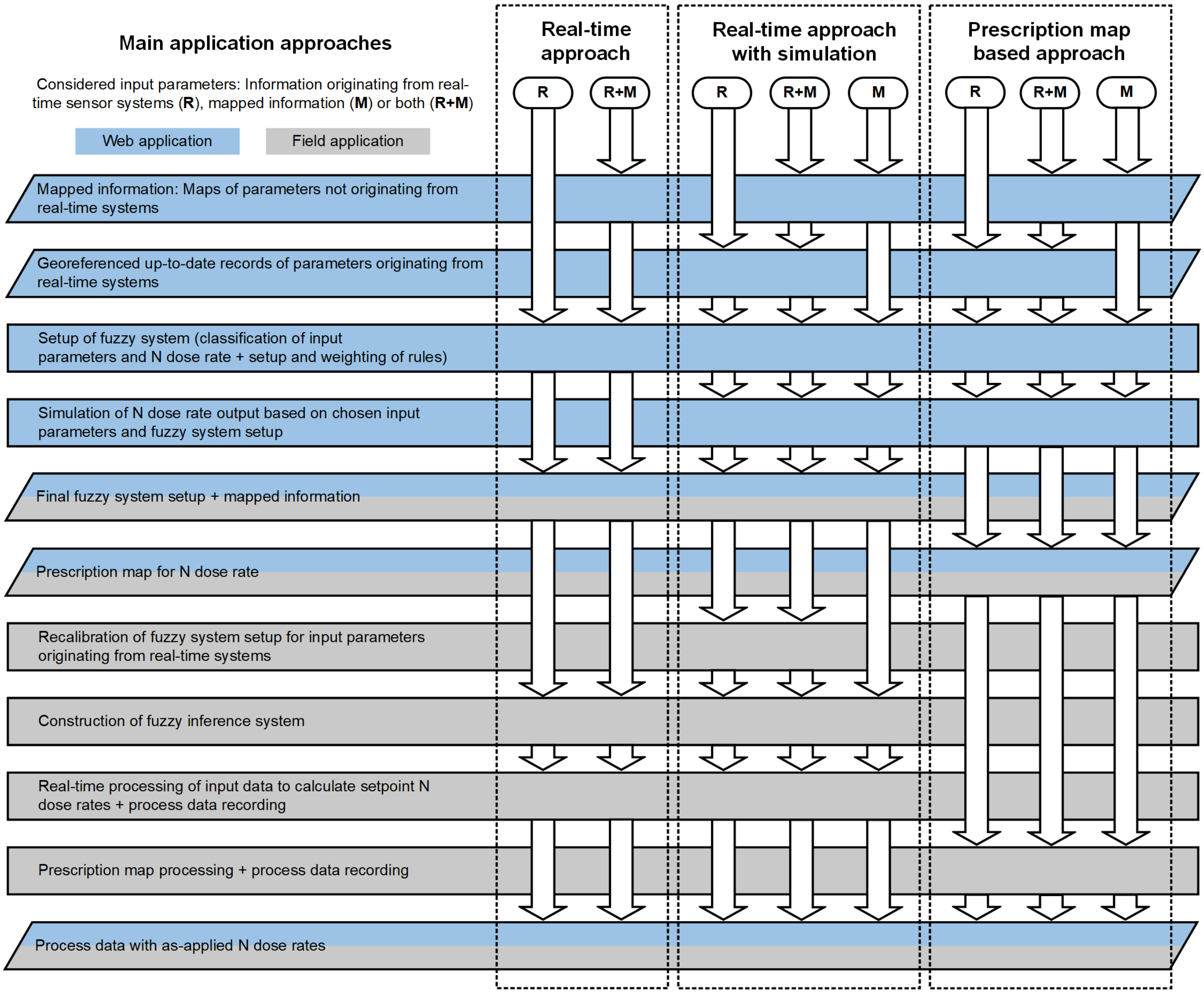

Figure 4.2. Flow diagram for the three main application approaches and their further differentiation according to the input parameters considered for VRNA.

Real-time approach

In terms of its technological principle, the real-time approach has analogies to common pure real-time sensor systems or those with map overlay, respectively. Even a real-time acquisition of e.g. soil parameters is also considerable (Adamchuk et al., 2011; Kodaira and Shibusawa, 2013), the focus is laid in the following on crop parameters acquired using real-time sensor systems as these are currently by far more relevant in this context. With a sole consideration of real-time sensor data, the process is initiated by a setup of the fuzzy system via the web application. It has to be considered that for this application approach, the user has to define the setup off the cuff, without any information about the spatial distribution of the crop parameter provided by the real-time sensor system. As these parameters are dynamic in time, the fuzzy system setup necessarily needs to be conducted in close temporal relation to the N application in order to avoid any systematic error resulting from a significant drift. Therefore, the user is likely to roughly pre-define the task after the field and crop assessment, at least in terms of the desired DR classes and rules. Based on the pre-configuration, the classification of the input parameter could be conducted at the field, right before the N application, after making measurements with the real-time sensor system at some characteristic spots. As outlined by Lundström and Lindblom (2018), preceding analyses of remote sensing data like e.g. satellite images could help to identify such areas and minimize the risk of a wrong calibration.

The probable time pressure for finalizing the system configuration immediately before the N application stresses once more the need to facilitate the decision making process via the GUI. In this context, algorithms to give a suggestion on the classification of the parameter delivered by the real-time sensor are considerable. Heiß et al. (2021) describe a method for giving such a suggestion with the aid of a fuzzy-logic based imitation of a real-time crop N sensor system's agronomic algorithms. The finalized fuzzy system setup is transferred from the web to the field application, where the fuzzy inference system is constructed after choosing the corresponding task. Subsequently, the N application process is conducted. When it is finished, the georeferenced records of relevant process parameters like the measured input values and calculated DRs are transferred back to the web application for documentation purposes and possible use in subsequent N applications.

The main distinctive feature compared to common real-time sensor systems is the full freedom that is given to the user in terms of the interpretation of the crop parameter concerning the DR for each specific N application. The difference is even more significant when additional mapped information is taken into account. This can include a wide variety from rather static parameters like quality grades from soil inventories or the field topography, but also dynamic ones like soil moisture or crop information from previous applications. While common systems have rather deterministic or simplified procedures in this context, the presented approach is theoretically capable of numerically fusing any amount of additional mapped information with the crop parameter acquired in real-time.

Real-time approach with simulation

The technological principles followed in the real-time approach and the one with a preceding simulation have big overlaps. However, the latter is significantly different in terms of configuring the VRNA's agronomic behavior because the expert gets an immediate feedback on the impact of the decision making in the web application's GUI. It is possible that, at least in certain areas of the field, the simulated results are adverse to the intended strategy and therefore the decisions can be adapted in an iterative process. In contrast to this, uncertainties about the spatial distribution of the crop parameter's values often remain in the pure real-time approach, which is a known issue and can cause the intended average N amount for the field to be missed significantly (Heege, 2013b).

In case that information from a real-time crop sensor is considered, a dedicated measurement prior to the decision making is required, which counteracts the temporal combination of measurement and N application as a main advantage of such systems. Still, it seems plausible that such records could originate from other preceding processes like e.g. plant protection. If, especially at early stages of the vegetation period, the crop's current N status is not informative enough (Heinemann and Schmidhalter, 2021), it can still make sense to consider solely mapped information. Even if it then seems more obvious to implement such a strategy with a prescription map based approach, it may well make sense to have the N application process being triggered by a real-time sensor system. First of all, the interaction with the applicator is quite different because SRs are defined at comparatively low time intervals. As outlined by Heiß et al. (2022), this results especially with centrifugal spreaders in special characteristics concerning the fertilizer distribution on the field, which might be preferred. Second, the user is likely to be interested in recording with the real-time sensor system to make use of the acquired crop data in subsequent N applications, at least as a supplementary source of information. In any case, when conducting an N application solely with mapped information using the real-time approach, the user would definitely make use of the possibility to simulate the results as all the necessary input for this would be given.

Regardless of the information considered for VRNA, the real-time approach with simulation is initiated by the setup of the fuzzy system in the web application, which is followed by the simulation of the DR output based on this setup and the chosen input parameters. The setup is then transferred to the field application, along with mapped information, if applicable. The field application needs to provide a possibility to recalibrate the fuzzy system setup in case that information originating from a real-time sensor system is to be considered. This feature is crucial because real-time sensor systems process absolute values of the measured parameter, which would the pre-records used for iteratively setting up the fuzzy system with the aid of simulations require to be up-to-date on a daily basis. If no significant changes of the spatial distribution of crop parameters can be expected, simplified procedures can be applied to recalibrate the setup right at the field with new measurements at characteristic spots. The subsequent N application on the field follows the same steps as the real-time approach without simulation.

Prescription map based approach

With a few more steps that can largely be considered as state of the art, the real-time approach with simulation can be further developed to a prescription map based approach. Alternatively, it can solely rely on mapped information considering crop-related parameters provided by satellite or aerial images acquired e.g. with UAVs. This would significantly expand the applicability of the system architecture presented in 4.2.1, because a majority of farmers applying precision agriculture is nowadays relying on such data sources for crop-related information. As in the case of a real-time approach with simulation, this approach raises the particular question of how mapped input data should be requested for the fuzzy inference and how the output DRs should be displayed as a map. When using real-time data, the georeferenced points of the corresponding input parameter can serve as a basis for this purpose, whereas when using interpolated mapped information alone, a regular point grid, adapted to the precision of the applicator if feasible, could be used. For the prescription map, on the other hand, a final interpolation of the DRs is crucial for processing in the field application. In the ideal case, this interpolation would take into account the used applicator's characteristic properties in terms of fertilizer distribution.

As in every other case, the fuzzy system setup is the initial process step. The subsequent simulation of the DR is then of particular importance because it virtually delivers the final prescription map. The calculated georeferenced DRs only have to be settled to the N content of the used fertilizer, interpolated and brought into specific required formats for further processing. For all of the subsequent steps, which encompass the transfer of the prescription map to the field application, its processing during execution of the N application in the field, as well as the feedback of recorded process data to the web application, commercial technology is already available. Consequently, today's variable rate application terminals could completely replace the field application presented in Figure 4.1 for the prescription map based approach.

4.3 Prototypical system implementation

4.3.1 Functional flow

Prior to the prototypical implementation of needed system components, a functional flow had been designed for the real-time approach with simulation because it covers all the elementary aspects of the conceptualised system. The design of the prototypic system's functional flow, as well as the subsequent GUI design involved experiences made in applying the fuzzy expert system presented by Heiß et al. (2021) in two seasons of field trials in winter wheat together with farmers and agronomic advisors. In Figure 4.3, the sequence of the individual process steps is schematically illustrated. The process chain started with the task management in the web application, where the possibility was given to reload and edit historic tasks, create new ones and give some basic task information. The subsequent stepwise fuzzy system setup generated key data describing the structure of a Takagi-Sugeno fuzzy inference system. This was based on the methodology presented by Heiß et al. (2021), where also the functional principle of such systems is described. The starting point here was a fuzzy logic based imitation of the Yara N-Sensor ALS2 real-time sensor system's agronomic algorithms, which was applicable for certain use cases in winter wheat and used the normalized sensor value (SN) corresponding to the N uptake of the crop in kg ha^{-1} as input. With the N-Sensor setup, the user was given the opportunity to automatically get a setup of a corresponding single-parametric fuzzy system suggested. As outlined in section 4.2.2, this can be especially useful in the real-time approach, where there is no information about the spatial distribution of the crop's N uptake.

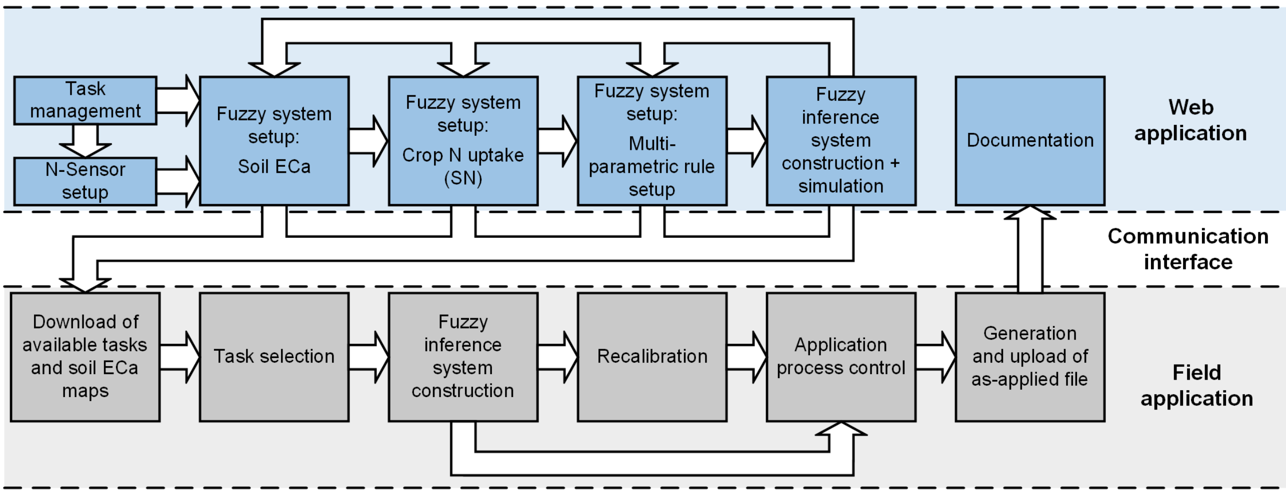

Figure 4.3. Schematic flow of the process chain realized with the prototypical system implementation.

In the next process steps, single-parametric fuzzy systems concerning the soil ECa and the SN, respectively, were manually defined. In case of the SN, an initial suggestion was given, if the N-Sensor setup had been conducted in advance. The prototypical implementation of the web application provided that all defined DRs are globally available in each setup step. Therefore, the DRs defined for the setup concerning one parameter could be used for the other one and supplemented by further dedicated ones, respectively. This was of importance, if the user desired to have a different range of DR variation for each parameter. Subsequently, in a multi-parametric rule setup, the user got an overview of all rules affecting the SN and ECa, respectively, via a matrix, which could be supplemented by further rules relating both parameters concurrently to the DR singletons defined before.

From Figure 4.3 it can be seen that all process steps related to the fuzzy system setup had to be accomplished in sequence by the user, implying a wizard process like Ferrise et al. (2021). It seems cumbersome regarding the fact that often only one parameter is to be considered but it makes the user reflect all possibilities for each specific task. To skip a parameter, the user only had to refrain from defining rules related to it, while the configurations concerning the input value and DR classification, which may have originated from previous tasks, could be left untouched. Alternatively, the user might intended to dispense with rules that apply to a single-parametric fuzzy system but consider the affected parameter in the multi-parametric rule setup. For this case, the input value and DR classification were still crucial.

The final process step that could be conducted before the execution of the N application on the field was the simulation of DRs. For this, it was needed to build a fuzzy inference system based on the gradually defined setup and apply it to mapped soil ECa data and SN records, respectively, in an inference engine. After analysing the results, the user had the opportunity to go back to the previous setup steps, make adaptions if needed and run the simulation again with the updated fuzzy inference system. In Figure 4.3, it is implied that the fuzzy system setup could be abandoned at each process step. For instance, the user may have wanted to conduct a bare real-time application considering the SN only, which would not require to define multi-parametric rules and make a simulation impossible. Therefore, the user was given the possibility to exit the configurations in the web application at each process step by saving the task with the current configuration. Via the communication interface, basic information and the fuzzy system setup assigned to the task, as well as the soil ECa maps assigned to the single fields, were transferred to the field application. If simulation results were available, it would have been straightforward at this point to interpolate them and transfer them as prescription maps via the communication interface for processing in the field application. As outlined in 4.2.2, this sub-process was regarded as widely state of the art and therefore not considered in the prototypical system implementation.

Via the field application's frontend, the user could select the task he wanted to conduct for a specific field, upon which the backend constructed a fuzzy inference system based on the fuzzy system setup deposited in the task. In case the N application was supposed to follow the real-time approach with simulation considering the SN as an input, the user was given the possibility to recalibrate the fuzzy inference system. Otherwise, the user could go straight to starting the application process control, which was implemented in a very similar manner as described in Heiß et al. (2022).

During the conduction of the N application, the field application georeferenced and recorded relevant process parameters, which were used to generate an as-applied file after the N application on the field was accomplished. This file was fed back to the web application via the communication interface, where the data were archived and presented to the user in the frontend.

4.3.2 Web application

4.3.2.1 Technical framework

For the implementation of the web application and the web-based data management, a containerization approach using the Docker virtualization software (Docker Inc., Palo Alto, CA, USA) was followed. Hereby, software code is incorporated into isolated packages containing all the necessary components such as libraries, frameworks and other dependencies, which basically makes it a fully functional portable computing environment. Within its container, the software is transferable to any infrastructure and can run there regardless of its environment or operating system.

A PostgreSQL 13 database with PostGIS 3.1 and associated raster extension was created as one container. It contained different master data for the web application's GUI such as fields, descriptive texts, ECa maps, SN records, simulation output data and trigger tables necessary for the simulation. While SN and simulation output data consisted of georeferenced point values, ECa data had been interpolated and were deposited as raster datasets. They were additionally converted to point features and stored with their coordinates in database tables, which was needed for conducting simulations considering the ECa only and had the advantage of enabling interactive adjustment of data presentation and evaluation in the GUI. In addition, all configurations assigned to tasks were stored in tables in the database. After saving a task, the associated configuration containing general parameters, as well as those required for the fuzzy system setup, was created based on the settings defined in the GUI and stored in the database.

The web application itself was implemented with the web app design package Shiny for R 1.6.0 (RStudio PBC, Boston, MA, USA). The framework was extended by the R package Plotly 4.9.4.1 for the display of map elements, whereby background maps and other information were obtained from OpenStreetMap. The Shiny R Studio application was also built as Docker image containing all necessary libraries. The content of the frontend GUI, as well as all possible operations such as value assignment, map evaluations and master data management were obtained from the PostgreSQL database.

4.3.2.2 Fuzzy system setup

After accessing the web application frontend via a web browser, all configurations available in the database were presented as selection list to the user. This was at the same time the list of all tasks that had been configured so far. Choosing an archived task as a starting point for the creation of a new one for the same field was considered as a straightforward approach because, above all, it spared to repeat the time-consuming classification of the input ECa, which is static as long as the same map is used. Then, the single GUI components of all the process steps that are assigned to the web application in Figure 4.3, were loaded based on the information deposited in the task. The whole web application GUI was organised in a single web page. For the task management and the N-Sensor setup, a static sidebar was used, while the single fuzzy system setup steps, the simulation, as well as the documentation were integrated in a tab group. To assist the user's decision making process, help buttons providing some basic information and instructions for operation were placed near to GUI elements with a higher need for explanation. In Figure 4.4, the layout of the web application GUI is presented. The fuzzy system setup concerning the single input parameters was the most crucial aspect in terms of the graphical implementation, whereby it was structured in a very similar manner for the SN and the ECa, respectively. To illustrate this process step by way of example, the GUI tab with the fuzzy system setup concerning the SN was chosen.

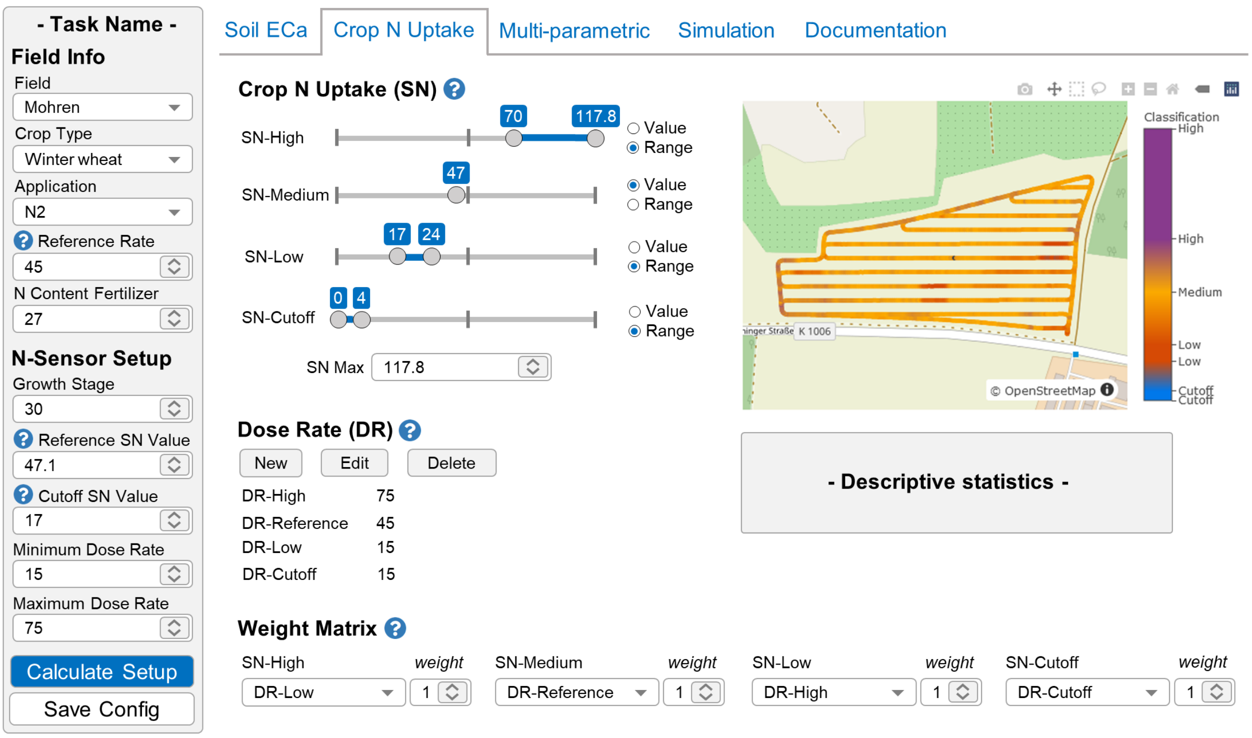

Figure 4.4. Layout for the one-parametric fuzzy system setup concerning the SN in the web application GUI.

In the sidebar, the field, the crop type, as well as the number of the split application could be chosen via dropdown menus. Further, the reference rate, which corresponded to the DR in kg ha^{-1} for a uniform application, as well as the N content percentage of the used fertilizer could be inserted. If an N-Sensor setup was desired, the user was able to provide the necessary parameters. Here, the reference SN corresponded to the value measured at a crop to which the expert would have assigned the reference rate, the cutoff SN indicated the value, below which the DR should be strongly decreased due to extraordinary lack of biomass and the minimum and maximum DR set the limits for the variation depending on the SN. After pushing the corresponding button, the web application backend calculated the fuzzy system setup for the SN according to the fuzzy logic based N-Sensor model presented by Heiß et al. (2021), whereby minor improvements were made in terms of the range of the input SN, which did not influence the model's functionality. Based on the calculated parameters, the settings for the classification of the input parameter SN, which was realized in the frontend GUI with a group of slider bars, the classification of the output DR, which was realized in tabular form, as well as the rules and their weights, which were realized in form of a matrix, were automatically provided.

According to Zhai et al. (2020), the ability to provide predictions and forecasts is an important quality criterion for agricultural DSS. As outlined in section 4.2.1, the weather is a crucial contextual information the expert needs to consider in order to adapt his decision to the prevailing conditions at each specific N application. Therefore, a weather service provided by the official agricultural administration (LTZ Augustenberg, 2022) was embedded via a HTML script as an external web resource into the tab for the one-parametric fuzzy system setup concerning the ECa because this was the first step of the fuzzy system setup according to the functional flow. The script was adapted to retrieve information for the weather station situated at the research farm 'Ihinger Hof' of the University of Hohenheim (48°44'41.61''N, 8°55'26.42''E), where also field trials had been conducted and experimental SN and ECa data had been acquired.

A further, very important source of information for the expert was the map presentation of input parameters, whereby for the temporally static parameter ECa always the same point map associated to the chosen field was used and for the SN, the most recent record available was loaded in the map view window. Below this, using the Shiny R function summary, descriptive statistics were presented to the user, which were related to the presented point map and specific subareas, respectively, that could be selected manually.

Map-based questioning is an effective way of collecting spatial expert knowledge (Oliver et al., 2012) and as a fundamental aspect of decision support, the color classification of the point maps was functionally connected with the value classification of the input parameters in the slider bars. For the

ECa, three bars with associated linguistic terms (*'low'*, *'medium'* and *'high'*) were given, where the total range of each one was defined by the minimum and maximum value from the ECa raster file. For the SN, there was additionally a fourth one (*'cutoff'*) and the total range of each bar reached from 0 to the maximum SN value calculated by the N-Sensor model or adjusted manually. For each slider bar, and thus input class or linguistic term, respectively, the most representative value or a range of the most representative values could be defined based on the user's experience and analysis of the input map. These values or ranges were assigned to a specific color of the colorbar associated to the map. For intermediate values, a shading with a gradual change from one color to the next was implemented. As soon as changes were made in the slider bars, the web application updated the color classification of the point map, thus giving an immediate visual feedback to the user. This way, the user was not only able to associate a linguistic term to specific areas within the field but could decide also how sharply the different classes should be distinguished. In Figure 4.5, the interaction of the input classification via the slider bars and the color classification of the map is illustrated in an exemplary manner with screenshots taken from the tab for the single-parametric fuzzy system setup concerning the soil ECa. In Figure 4.5a, the default classification with a single representative value for medium is shown, whereas this is changed in Figure 4.5b to a representative range significantly narrowing the transitions between the classes.

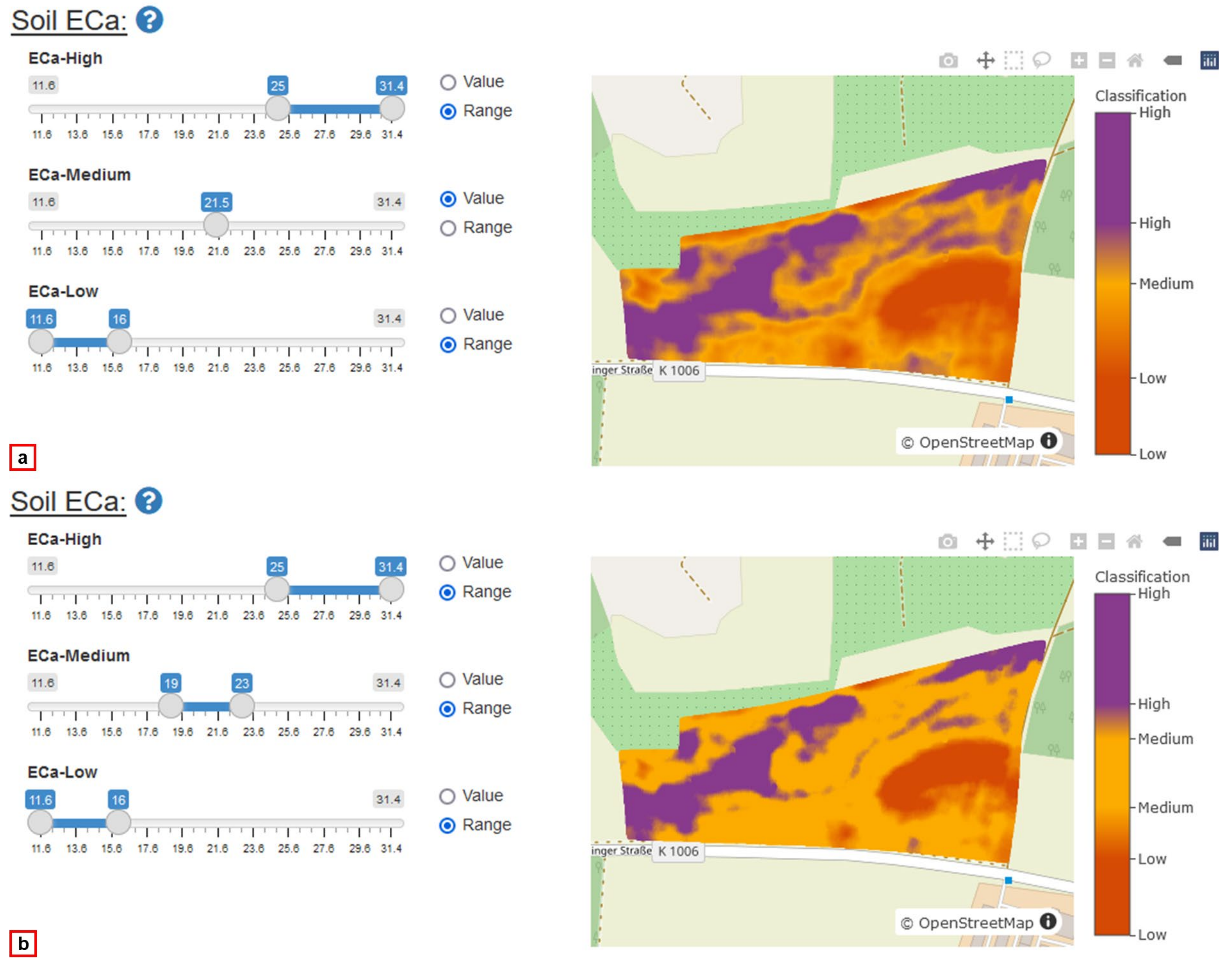

Figure 4.5. Input classification with instant visual feedback on the mapped input data with (a) the initial setting and (b) an assumed exemplary configuration for illustration purposes showing the effect of a broad range for the medium class and consequently narrowed transitions between the classes.

The consideration of blurredness in measured parameters is a characteristic principle of fuzzy systems and with a connection of the slider bars with the maps, a visualization tool to represent fuzzy zones with uncertainties in geographic and attribute space, as suggested by Guillaume et al. (2012), was given. Technically, fuzziness was implemented with membership functions deduced from the settings in the slider bars. Depending on the choice of the most representative value or range for a class, the feet as well as the peak or shoulders of triangular or trapezoidal membership functions, respectively, were defined. In Figure 4.6, this process is illustrated schematically for an exemplary constellation for the input parameter SN. To simplify the configuration via the slider bars as much as possible, thus avoiding overload of the expert, the linearly inclining parts of the membership functions represented straight connections between the peaks or shoulders of adjacent ones. This is a common approach applied in fuzzy systems for modeling and controlling agricultural processes (Bouroubi et al., 2011; Tagarakis et al., 2014). Further, experiences with the fuzzy system presented by Heiß et al.

(2021) in different fields and N application scenarios have shown that a more detailed description of the membership functions does not bring a gain in achieving the desired fuzzy system characteristics.

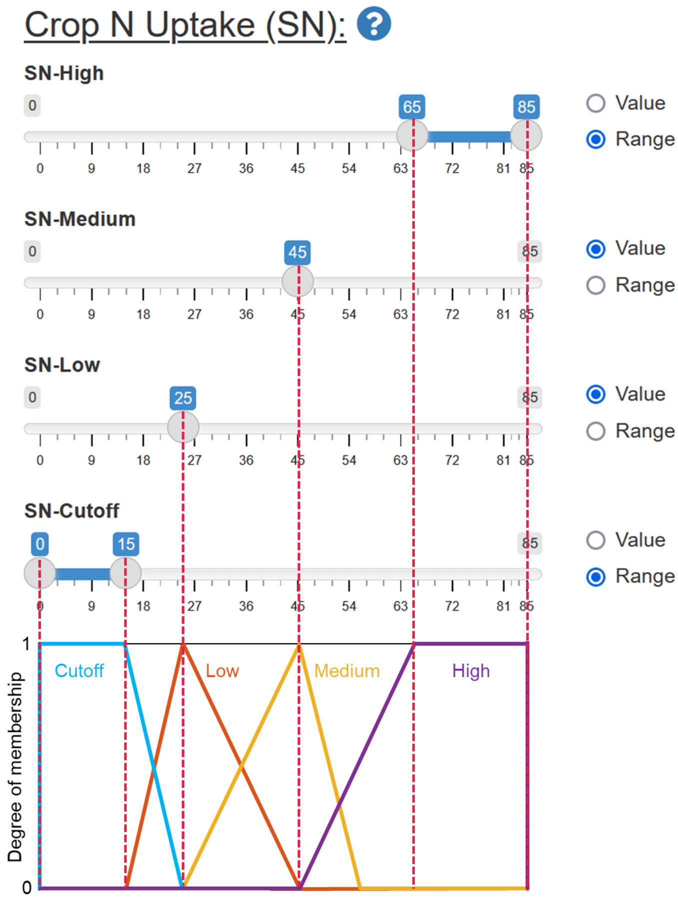

Figure 4.6. Schematic illustration of the input membership function setup via the web application frontend.

As the fuzzy systems were based on Takagi-Sugeno inference, the output DR was classified in singletons. As shown in Figure 4.4, this was realized by providing in each single-parametric fuzzy system setup a table to the user, where new DRs could be added and labelled as desired, edited or deleted. The definition of the interrelations between the input categories and the DR singletons, and thus the fuzzy system's characteristic behavior was defined by the rules. For this, a matrix was given, where the expert could choose for each input category the desired DR value from all available ones via a drop-down menu. As described in detail by Heiß et al. (2021), the logic connection was based on 'IF-THEN' conditionals, which could be supplemented by weights ranging between 0 and 1 to take into account the relative significance of single rules.

By conducting a complete fuzzy system setup for each input parameter, a multi-parametric fuzzy system was already characterised, which could be further refined in the dedicated GUI tab for multi-parametric rule setup. In a two-dimensional matrix, the expert got an overview of all rules with their weights that had been defined in the single-parametric fuzzy system setups. As an extension, multi-parametric rules could be added by assigning an available DR, as well as a weight to a combination of fuzzy sets from the soil ECa and the SN, whereby the logic connections followed 'IF-AND-THEN' conditionals. With this feature, the user could address contradictory interpretations of input values at specific areas of the field and respond to different causes of plant stress, which is a major challenge in VRNA (Pedroso et al., 2010; Adamchuk et al., 2011). As an alternative, the possibility was offered to completely skip the single-parametric rules and define the system behavior only with multi-parametric ones. In Figure 4.7, a screenshot from the GUI tab for the multi-parametric rule setup is shown. This originated from a specific use case of a field trial at the second split N application, where the expert intended to give more importance to the input SN by halving the weight of the rules affecting the ECa. The varying importance of single parameters even during the season was also stated by Isensee et al. (2003) and can easily be addressed with the weighting functionality.

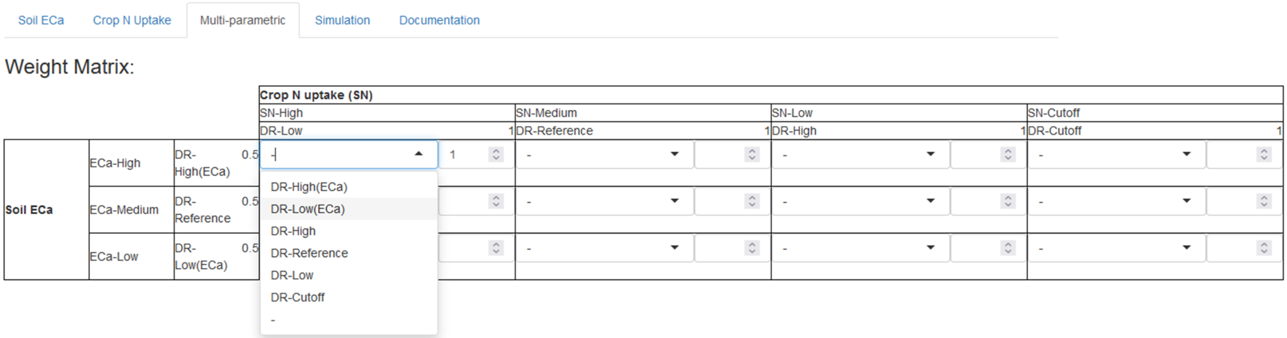

Figure 4.7. Matrix for setup and weighting of multi-parametric rules in the web application GUI.

4.3.2.3 Simulation

The simulation of DRs based on the fuzzy system setup and the available input data followed a specific workflow, where the data integration software Talend Open Studio 7.31 (Talend Inc., Redwood City, CA, USA) was used to enable the interaction of different components. Through the initialisation of the simulation via the GUI, a database entry was generated, which finally started the data integration workflow. Hereby, the soil ECa raster file, as well as CSV files containing all necessary parameters of a task to describe the fuzzy system setup, the ECa point map information and the latest N-Sensor record, respectively, were provided in a dedicated local file directory on the server. For downloading of the needed data from the database and providing the corresponding files, a communication software was developed using Python 3.9.6 with Anaconda 3. The same software was used also later on in a slightly modified form to accomplish the communication interface between web and field application. A stand-alone fuzzy inference engine processed the data deposited in the file directory and dropped there a CSV file containing the georeferenced DRs. The data were uploaded to the database by the communication software for being presented by the GUI in a Plotly map viewer together with a panel of descriptive statistics. In Figure 4.8, this is illustrated with a screenshot taken from the simulation tab.

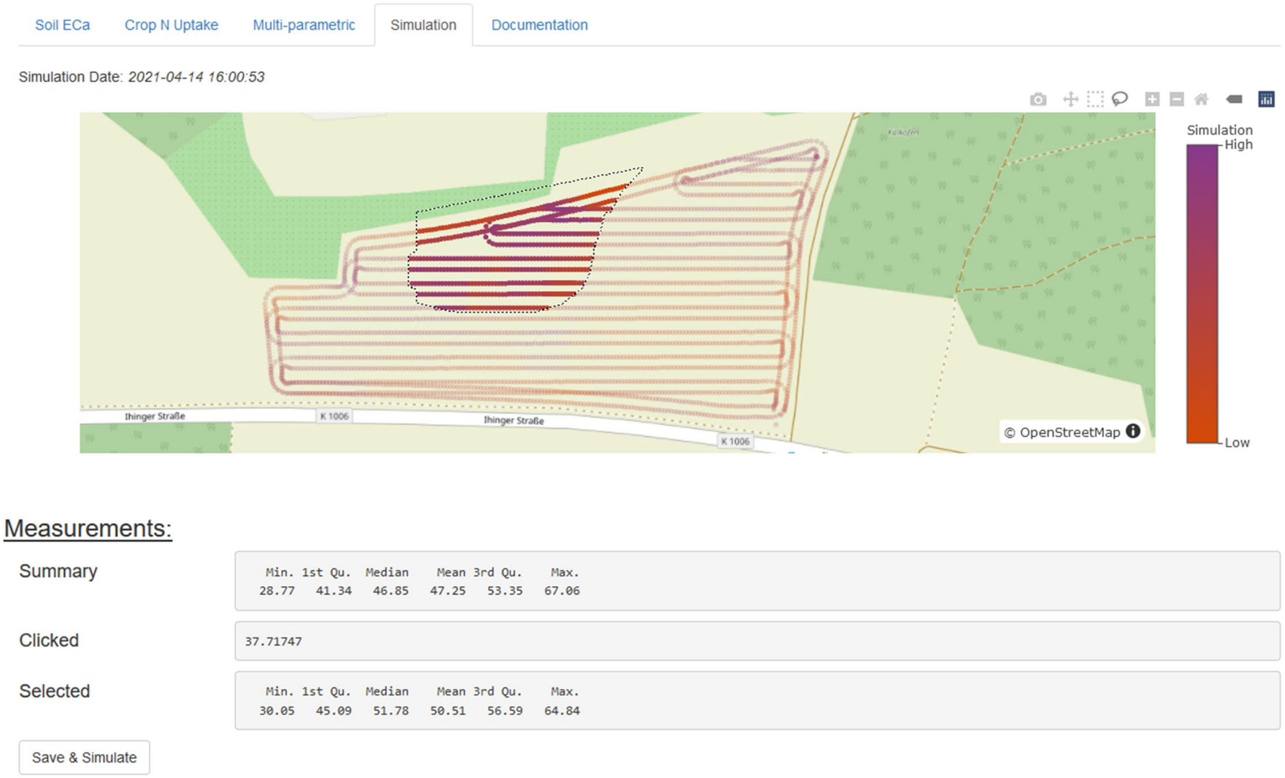

Figure 4.8. Simulation tab in the web application GUI.

The stand-alone fuzzy inference engine was developed in MATLAB R2021a (The Mathworks Inc., Natick, MA, USA) with the aid of its Fuzzy Logic Toolbox, then compiled as Java archive using its Compiler SDK and finally installed on the server as Java class together with the MATLAB runtime 9.10. Its functional flow was first based on parsing the task file to extract the fuzzy system setup and construct a fuzzy inference system as described in Heiß et al. (2021). The 'AND' conjunction in multi-parametric rules, which, as mentioned in section 4.3.2.2, were an extension to this work, was thereby interpreted mathematically as the product of the fuzzified input values (The Mathworks, 2021). The subsequent procedure for simulating the DRs depended on the input parameters to be considered. In case that the fuzzy system configured in the web application had only the soil ECa as an input, DRs were simulated based on the soil ECa point map deposited in the database. For fuzzy system setups, where the SN was involved, the real-time data fusion approach presented by Heiß et al. (2022) was largely adopted because the same system setup was used in the present work for recording N-Sensor data and as a model setup for implementing the compartment of the field application, which was responsible for controlling the fertilization process. If only the SN was considered, for each of the recorded absolute positions of the GNSS antenna within the N-Sensor record, the corresponding absolute sensor position was defined and the DR calculated from the deposited SN value was assigned to it. In the case of a multi-parametric fuzzy system setup, DRs were defined for two subsections within the sensor-spreader system at each recorded point within the N-Sensor record. For this, two ECa values queried from the raster file were fused each with the SN value in the fuzzy inference system. In front of the background of corresponding considerations formulated in chapter 4.2.2, this framework for presenting simulated DRs can be considered as one that is very much adapted to a specific sensor-spreader combination.

4.3.3 Field application

A laptop with a 64-bit Windows 10 Pro operating system, equipped with an Intel Core i5-8250U at 1.6 GHz processor and 8 GB working RAM was used as controller platform for the field application. To realise the communication interface for data exchange with the web application, a slightly modified version of the communication software described in section 4.3.2.3 was installed. Tasks were created in the Windows Task Scheduler to attempt automated exchange of the latest relevant data, as soon as the controller platform had network connection. Both, upload and download were initiated with the execution of batch files that called the necessary Python scripts for communication with the database on the server and execution of necessary data processing routines. In the download process, all available task CSV files at their latest state were retrieved and stored in a local folder. The folder with all the soil ECa raster data was only updated to its latest state, if there was a change in the datasets available in the database. In the upload procedure, all the as-applied CSV files that had been generated by the field application were transferred from the corresponding local folder to the database. There they were assigned to a specific task and presented in the documentation tab of the web application GUI in the same way as the simulation data. Beyond that, the controller platform was used to record SN data in the same way as described in Heiß et al. (2021) and transfer them to the database using the same procedure.

The field application was implemented in MATLAB's App Designer. Its frontend was structured in tabs and is presented in Figure 4.9, where Figure 4.9a is showing the tab for task management and Figure 4.9b is showing the tab for operation of the system during the fertilizer application. Via a panel on the right side within the task management tab, the user was given the possibility to manually conduct the data exchange with the web application, whereby the download and upload processes were the same as described for the automated data exchange. The manually triggered data exchange was of special importance for the upload of N-Sensor records because the sole recording with the N-Senor software was decoupled from the field application. Only via the data exchange menu, a record could be assigned to a field and transferred to the local folder for upload to the database.

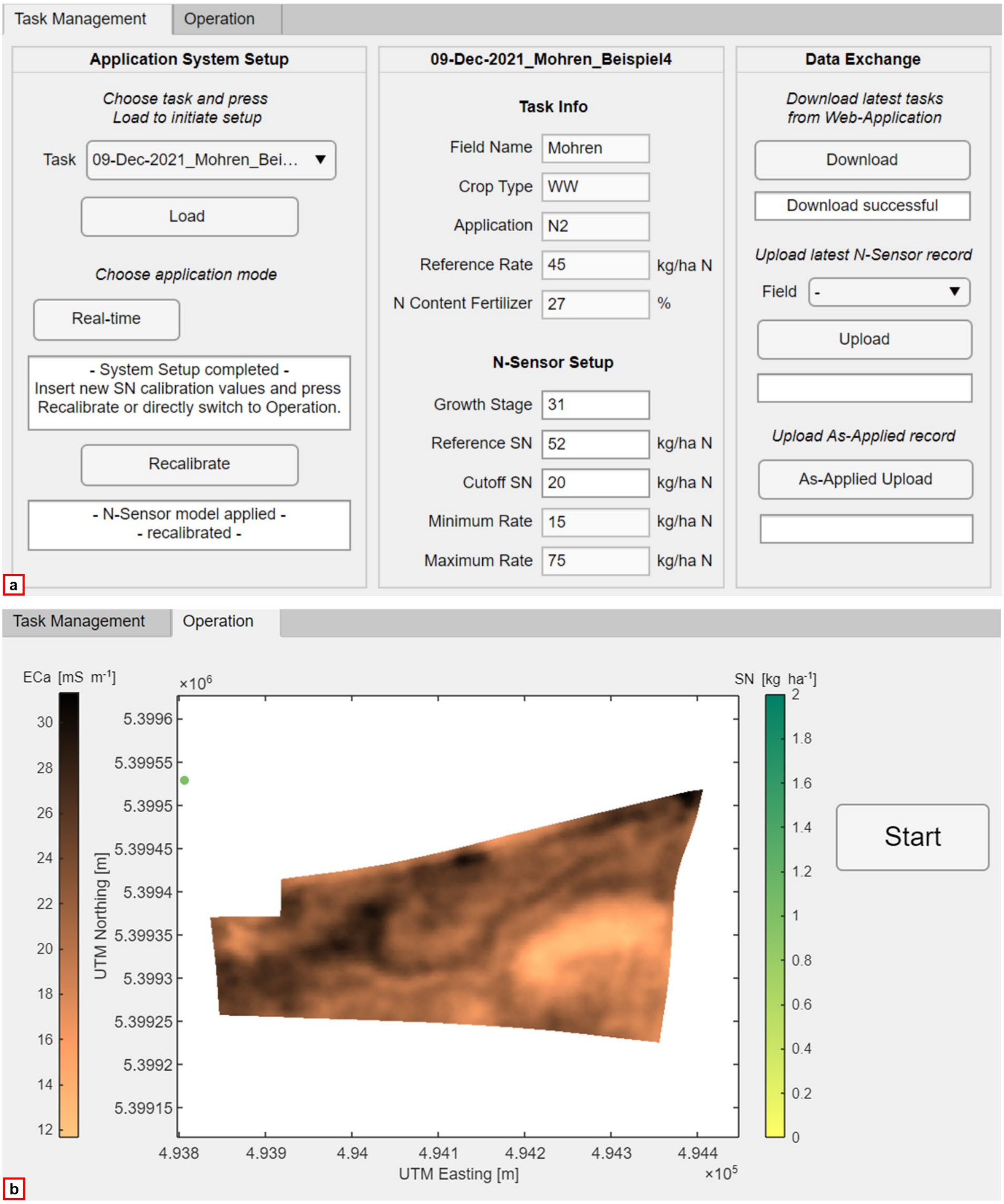

Figure 4.9. Field application frontend with (a) the task management and (b) operation tab.

Prior to the execution of a specific N application at a field, the user started in the task management tab with the application system setup, which was supported by information provided in a further, dedicated GUI container. In order to guide the user through this setup process, it was broken down to partial steps, where the necessary GUI elements appeared gradually and only if they were really needed. After choosing and loading one of the available tasks, in the GUI backend, the corresponding CSV file was parsed and the values of parameters, which had been defined in the web application GUI's field info and N-Sensor setup sidebar, were extracted. Thereby, the task information was always presented and the N-Sensor setup information only, if the SN was considered as input parameter. Further, a fuzzy inference system was constructed in the same manner as described in section 4.3.2.3 for the stand-alone fuzzy inference engine on the server. In the application system setup container, provision has been made for the possibility of choosing between a real-time and a prescription map based application, whereby only the real-time approach was implemented by adopting the system setup and real-time control algorithm applied by Heiß et al. (2022). These were supplemented by the differentiation of sections depending on the considered parameters, as already described in section 4.3.2.3.

If the SN was involved as an input parameter, the user was able to insert updated values for the growth stage, as well as the reference and cutoff SN value in the N-Sensor setup information in order to recalibrate the fuzzy inference system, which only affected the membership function setup of the SN. An algorithm in the field application's backend defined first, if the membership function setup for the SN had been calculated using the fuzzy logic based N-Sensor model. In that case, it was recalculated using the new calibration values in the model. Otherwise, only the feet, as well as the peaks and shoulders, respectively, of the membership functions were adapted based on the difference between the initial and the new reference SN value. This simplified approach was considered appropriate, as long as the time period since the initial decision making in the web application was short enough to justify the assumption that there had been insignificant changes in the spatial distribution of the SN.

Once the application system setup was complete, the user could switch to the operation tab, where the soil ECa map of the corresponding field was presented in case it had been considered as an input parameter in the fuzzy system setup. By starting the operation, the real-time control was initiated in the backend. The corresponding algorithm calculated SRs based on the fuzzy inference system, as well as incoming SN and soil ECa values, respectively, and coordinated their transmission to the applicator. After stopping the operation, an as-applied CSV file containing georeferenced SN, soil ECa and SR values was created, assigned to the active task and stored in the local folder for later transfer to the server. An additional functionality of the real-time control was provided to plot the georeferenced DRs and SN values, respectively, in real-time. In field tests, however, it turned out that the prototypical implementation using the App Designer did not allow this without a significant deterioration of the real-time control's performance.

4.4 Discussion

The strong user-centeredness of the presented system sets high requirements on their agronomic expertise and experience, as well as their knowledge about the conditions at a specific field. These factors significantly affect the reliability of their decisions and carry a significant risk for an inappropriate VRNA strategy, if they are not met. The need for a high quality of expert knowledge when incorporating it in DSSs was also given to concern by Colaço et al. (2021) and Lindblom et al. (2017). Especially a collaboration of farmers with professional agronomic consultants should provide these preconditions (Shanahan et al., 2008). An affinity for precision farming technologies, as well as a motivation to deal with the analysis of precision agriculture issues and achieve higher N recovery with the aid of VRNA are further requirements. Pesonen et al. (2008) found in a Finnish study that this is unconsciously present in many farmers.

According to Guerrero et al. (2021), also the subjectivity and inaccuracy of expert knowledge comes with certain risks. Fuzzy systems, however, are a predestined technology to handle these. Still, it is never guaranteed that every possible situation can be properly interpreted by the user and even if all the necessary conditions regarding the user's expertise are given, as in all systems related to VRNA, a reliable weather forecast remains the linchpin for success (Colaço and Bramley, 2018). A further pitfall of the user-centeredness is the significant additional workload due to the system configuration during an already labor-intensive seasonal period, especially when there is no external support from advisors. This might be a critical factor concerning the adoption of such a technology (Lindblom et al., 2017).

To cope with all these challenges, the formulation of the basic system architecture provided some fundamental considerations on possible technical solutions. These were further specified and illustrated in the prototypical system implementation, which incorporated experiences made with agronomic experts in applying the fuzzy expert system presented by Heiß et al. (2021). A central role has the web application's frontend aiming at straightforward decision making by clear GUI design, efficient information supply and feedback, as well as the facultative proposal of configurations concerning the SN. However, the streamlined GUI design also comes along with a certain rigidity concerning the flexibility in the configuration. For instance, the number of input membership functions and output singletons is fixed and cannot be adapted according to the user's preferences. Especially as further parameters get considered, the complexity of decision making will increase significantly, which is likely to require substantial enhancements in the functional flow and especially the multi-parametric rule setup. The prototypical implementation largely meets the requirements for agricultural DSSs discussed by Zhai et al. (2020) and Ferrise et al. (2021) but it must be seen more as a first draft than as a blueprint for a qualitative system. Beyond the GUIs, which should involve further enhancements with user experience design and get more resilient against user mistakes, certain core elements of the technical framework, which bring performance and stability issues, are also critical. The computational efficiency of the prototype system can be considered sufficient regarding the usability required in the context of this research. Consequently, sufficient performance should be ensured a fortiori after the implementation on platforms that are suitable for a qualified system.

Another means of relieving the user was the reduction of manual input by automating the entire VRNA process chain using digital tools embedded in an internet-based data infrastructure. However, especially for rural areas, the lack of reliable internet supply is still an issue (Paraforos and Griepentrog, 2021; Rose et al., 2016). This can be critical especially if the VRNA configuration via the web application is supposed to be conducted directly at the field. Further, the prototypical system implementation of the web application and the communication interface is in general still a quite closed system in terms of the used software interfaces and data formats, thus limiting e.g. the capacities of data exchange automation. Specifically for further processing in the fuzzy system, the alignment of heterogeneous data from various different sources, having varying spatial resolutions and formats is a fundamental prerequisite and not a trivial task to accomplish (Guillaume et al., 2012). The work of Bökle et al. (2022) describes a pathway for integrating distributed data sources and IT structures in a decentral digital farming system and defines possible strategies for improved scalability and interoperability. This affects also the controller platform and in particular the field application, which was tailored to a specific sensor-spreader system.

4.5 Conclusions

The presented conceptual system architecture describes fundamentally new opportunities to consider expert knowledge for a fusion of multiple relevant input parameters for VRNA. This affects not only the adaption to dynamic environmental conditions but also to different production targets. Further, the concept provided considerations on automating the entire process chain of VRNA with the aim of easing data management, decision making and task execution on the field, thus looking at all relevant aspects of a user-centered site-specific N management system from a holistic perspective. The systematic reflection of various and partly unusual but still plausible scenarios has shown the high versatility of the approach in terms of used input data and application approaches, which is an important factor for its adoption considering the variety of sensors and precision agriculture data used by farmers. The prototypical system implementation, which was designed for the case of a real-time application with simulation, has verified the consistency of the concept. It has illustrated the technical realization of core aspects along the whole process chain and specifically concerning the decision making in the web application. At the same time, possible pitfalls, as well as technical requirements on a qualified system were revealed.

The concept has fundamental differences to common VRNA approaches but its generic and flexible properties allow a straightforward combination with other techniques, which could aid in eliminating the weaknesses in each case. For instance, models providing mapped yield expectation or soil moisture could be incorporated by having them as a further input parameter among others. By providing basic strategies with static, universally valid pre-settings that could be further refined, significant reductions in the user effort for system setup could be achieved, especially if more parameters get involved. To validate the benefit of the approach in terms of achieving a desired production target, comprehensive agronomic trials including different experts need to be conducted in the future with the system being implemented in a qualified form. Recent promising progress in the field of artificial intelligence make it seem possible to integrate self-learning algorithms or use the system as an effective tool to combine expert knowledge with e.g. machine learning, hence heading towards more robust hybrid DSSs for VRNA.

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CHAPTER 5

General discussion

5.1 Definition of variable rate nitrogen application strategies in a fuzzy expert system

The broad and successful use of fuzzy systems in various research on agro-environmental systems and their evident suitability for the integration of expert knowledge motivated the development of a VRNA system with highly user-centered agronomic algorithms to be based on this technology right from the beginning. Regarding the entire VRNA process chain, this is the core element of deciding on the basic system behavior and therefore, a systematic approach was followed to develop and technically analyse a methodology for setting up a fuzzy expert system. As a starting point, the imitation of an established VRNA system's algorithms was pursued to get an impression of how it would reveal itself to the user in the form of fuzzy logic and validate the usability of this approach. The Yara N-Sensor ALS2 system was chosen because it covers the aspect of real-time sensor systems as one of the main technologies used in the field of VRNA. Beyond that, the first N-Sensors had been commercialized more than twenty years ago and the underlying agronomic algorithms have ever since undergone evaluation and improvement under practical conditions.

As these algorithms are based on piecewise linear relationships between sensed crop N uptake (SN) and the DR, the identification of their fuzzy logic based imitation for specific use cases in winter wheat was based on clear mathematical models concerning the membership function setup of the input parameter SN, as well as the calculation of DR output singletons. This also explains the high level of concordance achieved by the model in the comparison with various N-Sensor recordings made under real conditions with a high prevailing variation in the SN. Values of over 99% were consistently achieved for the Pearson correlation coefficient and the percentage root means square error reached a maximum of 0.14%. If the relevant calibration values are given appropriately, this model provides a realistic classification of the SN in membership functions, which is specifically important if there is no prior information about its spatial distribution in a bare real-time application. Furthermore, a way to transform the algorithms into a form adapted to human cognition, allowing intuitive adaptation and fusion with other parameters was given. The developed principles of identification and validation of a fuzzy logic based model are basically transferrable to other agronomic algorithms. This is also where the early commitment to Takagi-Sugeno inference pays off, which comes with slight limitations in terms of adaptability, but is an important basis for the incorporation of further, and in particular automated, decision support (Sivanandam et al., 2007).

For the extension to a multi-parametric fuzzy expert system, the soil ECa was considered predestined for theoretical considerations in the scope of a study case. It is a very well-researched, composite indicator for soil attributes that can effortlessly be acquired at a high resolution and requires a profound knowledge of local conditions to interpret it based on prevailing weather conditions in terms of productivity potential (Heil and Schmidhalter, 2017). Specific assumptions were made to relate to scenarios with an assumed reaction of the expert to the weather-dependent availability of water. The subsequent map-based and numeric analysis had a strong theoretical character as any validation of benefits concerning yield, economic return or environmental impact would require several years of comprehensive field trials. Still, the analysis revealed that by combining rules referring each to only one parameter, mutual interactions and the combined relationship to the DR can be represented in a straightforward manner and that the parameter fusion can find a compromise between the decisions resulting from the one-parametric systems. Further, it became evident that including soil information can reduce the known risk of under- or over-fertilization due to incorrect calibration of the real-time sensor. Also, the effect of possibly erroneous decisions of a single-parametric system under certain conditions can be mitigated by considering multiple parameters.

5.2 Technical implementation of data fusion and precise application

In order to rapidly achieve broad impact with novel VRNA techniques, a focus must lay on their in-field implementation, whereby from a pragmatic point of view, application systems with a current and foreseeable high dissemination should be considered. Therefore, the combination of an N-Sensor with a tractor and centrifugal spreader, which are both interconnected via ISOBUS, was chosen due to its exemplary nature as a basis for examinations on a control implementation of the previously developed fuzzy expert system, as well as models for enhanced spatial synchronization of DR determination and application.

The basic principle of a fuzzy logic based N-Sensor model in combination with a case-specific interpretation of the soil ECa was further pursued and applied to a real use case from a field trial. As a possible technical solution to address sub-field peculiarities regarding the interpretation of the ECa, a geofence was introduced, which is close to a hybridization of the fuzzy expert system with a management zone approach. Investigations on increasing the lateral resolution of sensing and DR determination highlighted that a compensation of the limited areal coverage of real-time sensor systems with an oblique arrangement of individual sensing heads usually requires them to work together as an overall system as there might be interactions with systematic structures in the crop canopy. As a consequence, due to the mere differentiation of ECa values in the scope of investigations based on real measured data, there were only marginal differences in the DRs within the working width, which had been expected also based on previous findings (Griepentrog et al., 2007).

The analysis of technical latencies and spatial offsets within the two dedicated sections of the entire application system revealed the strong interdependencies between the real-time sensor and GNSS data acquisition, request of mapped soil ECa data, and inference on the DR and SR control of the spreader. Simplified procedures were applied to consider the main time-affected processes within the latter because the focus was not on their highly accurate determination but their basic representation within a generic control algorithm for dynamic offset optimization. Consequently, the response of the spreader was not considered either because this depends on many manufacturer-specific uncertainties. Rather, the appearance of the SRs on the ISOBUS allowed a more accurate evaluation of the performance of the odometry-based control in terms of correct timing. The operability of the data fusion and dynamic offset optimization algorithms was proven in comprehensive field tests with different driving speed scenarios going in parts well beyond normal use. The cyclic georeferenced DR determination and theoretical application have shown a high consistency. Their deviation in the longitudinal direction never exceeded 1.5 m and exceeded 1 m in only 2.3% of the cases within the worst dataset. For a constant speed of 12 km h^{-1}, which was recommended by the spreader manufacturer, the medians of the deviation were in the range of 0.25 m, which corresponds to only 7.5% of the distance between subsequent processing cycles executed at 1 Hz.

From a practical perspective, deviations in this magnitude are irrelevant because centrifugal spreaders are averaging the subsequent DRs in real-time application due to their characteristic of applying on a large plane. It is arguable whether this applicator type is therefore suitable for this kind of investigation. However, inherent to their way of applying is an interpolation similar to kriging (Goense, 1999) and this should even be advantageous the more fuzziness is existing in the input data. Nevertheless, the presented offset optimization shows potential in achieving lower application errors, which should become even clearer when transferring it to pneumatic spreaders or sprayers. To mitigate the highly stochastic character in terms of the developed real-time control's accuracy, the implementation on a platform that can handle hard real-time constraints would be required.

5.3 Implications on a user-centered process chain for agile N management

The explicit user-centeredness due to the fuzzy expert system as a functional core required an analysis of the user's interaction with individual system components, as well as their integration in a consistent VRNA process chain. Based on that, an architecture was conceptualized, which described basic requirements in terms of the definition of the VRNA's agronomic behavior, execution of the N application in the field, documentation and data management. At the same time, the concept left as much freedom as possible concerning the specific technical implementation. Even though it may have a rather redundant character, a systematic analysis was added to address the variability in possible application approaches, as well as data types for the input parameters to be considered. This supplementary examination was very helpful in verifying the versatile applicability of the concept and being aware of possible pitfalls that require further technical specifications to be addressed.

Prior to the prototypical implementation of the concept, a functional flow of the entire process chain to be represented was designed. The existing framework for data fusion of N-Sensor and mapped soil ECa data was used as a model case for a multi-parametric real-time application with preceding simulation to create the most complex scenario possible for the concept's evaluation. The implementation of the web application's frontend can be considered the crucial part as this should provide a GUI for the efficient and direct acquisition of expert knowledge to automatically define a machine-readable fuzzy system setup in the backend. There, the experience gained in applying the fuzzy expert system together with agronomic experts in the scope of field trials was also incorporated. This stressed the sufficiency of using only triangular and trapezoidal membership functions, which had already been noted by Kahlert and Frank (1994), to keep the knowledge acquisition simple. For the same reason, an automatic full overlap of the legs of adjacent membership functions was used, which is also a common approach for fuzzy systems in the agricultural domain (Azaza et al., 2016; Tremblay et al., 2010). The basic structuring of the web application's GUI in tabs made it possible to have all submenus, including further steps like simulation and documentation, available on one interface and to switch directly between them. In general, the prototypical implementation aimed at an exemplary illustration of the concept and was therefore restricted e.g. regarding the data management, which did not allow analysis and consideration of relevant data from previous applications as suggested by Ostermeier et al. (2007).

The fuzzy classification of the input parameters was supported by instant visual feedback via a map. Thus, in contrast to fuzzy c-means classification, which is often applied in the creation of management zones but is not specifically suited to geodata (Guillaume et al., 2012), a method was provided to represent blurredness in the input data and address dynamic spatial patterns, as well as areas with specific characteristics in a kind of map-based questioning as suggested by Oliver et al. (2012). The multi-parametric control setup provided another way to address this. Especially with regard to the soil ECa, this is of importance because the interpretation of this parameter can be contrary even within a field (Pedroso et al., 2010). The changing relevance of individual parameters was addressable in a simple way by assigning a corresponding weight in the rules. With the simulation feature in the web application, the user was given the opportunity to get immediate feedback on the impact of the decisions and improve them iteratively in the sense of re-planning (Zhai et al., 2020).

The approach of a clear GUI design hiding all the functional complexity in the backend was also followed in the field application to relieve the user and avoid cognitive overload. Similar to the web application, all necessary menus were placed on one surface and, in the sense of an adaptive GUI, individual graphical elements were added successively as soon as they were required due to previous user actions. The user was given the possibility to control the exchange of configurations and geodata with the web application centrally from the field application. As a fallback level, there was an automatic cyclic data exchange in the background to cater for patchy internet coverage and also to have the most up-to-date data available, even if the data retrieval was accidentally forgotten by the user. Further, algorithms were implemented to readjust input membership functions based on new calibration values, which is of high practical importance with respect to real-time information.

Agricultural DSSs are still caught between little attention to expert knowledge, which severely limits the possibilities of flexible adaptation to situational conditions, and the operational risks, as well as the potential frustration that a strong user-centeredness entails if the high demands on the quality of expert knowledge cannot be met and too much additional effort is required (Pashaei Kamali et al., 2017; Colaço and Bramley, 2018). The presented concept aimed at mitigating these as good as possible by technical means supporting the user in the decision making, minimizing manual effort along the entire process chain and staggering the overall system with a web-based infrastructure, which enables also the interoperability with further DSSs. It thus fulfills the essential requirements as defined by Zhai et al. (2020) and in particular their demand for increased consideration of uncertainties and the use of expert knowledge. Still, this cannot compensate for deficiencies that arise with regard to the user's basic suitability as an expert or concerning the quality of the supplementary information, such as weather forecasts. Another critical aspect is that with increasing automation and mechanization, as well as contracting, users run the risk of moving away from operational processes and thus losing the sense of specific relations in individual fields (Heijting et al., 2011). However, the presented approach explicitly addresses also consultants who can help identify these (Ostermeier, 2013).

5.4 Outlook

With the fuzzy expert system as the technological core, new ways were paved for a numerical fusion of relevant agronomic parameters and the use of expert knowledge in an N management that can be adapted to the inherent spatiotemporal dynamics in a reactive and proactive manner. The consideration of further parameters should make the system increasingly reliable but at the same time more complex in terms of usability, which may require defining generic pre-settings that can then be supplemented by the user depending on the situation. Comprehensive agronomic validation in field trials is a necessary future step but requires further improvements, especially in knowledge acquisition, where further developments with regard to user experience need to be made in collaboration with versed agronomic experts (Welte et al., 2013; Oliver et al., 2012). The quality of expert knowledge is also expected to improve with further advances in yield, N mineralization and weather forecasting because these are very important parameters for decision making (Lukina et al., 2001; Colaço and Bramley, 2018).

The implementation as a real-time capable control algorithm enables the realization of the VRNA strategy in the field while also allowing the precise addressing of small-scale variations as defined by the user. The odometry-based approach principally opens up the possibility of including the driving speed as a further control variable for the applicator in the sense of tractor-implement-management according to ISO 11783. As an established standard for electronic communication in agricultural engineering systems, the latter also offers the possibility to solve multi-parametric real-time fusion via peer control and the exchange of relevant task information with the ISO-XML format (Paraforos et al., 2019). Its use should be promoted in further implementation steps together with suitable APIs along the whole VRNA process chain to enable better interoperability with external systems, as well as better integration into existing agricultural IT infrastructures (Bökle et al., 2022).

Although especially the strong user-centeredness of the overall system can be considered a radical counter-design to previous techniques, it does not question them fundamentally. Since reliable, fully automated decision-making is not to be expected in the mid-term either, the aim should rather be to harmonize different approaches to create even more robust systems. The inclusion of the N-Sensor's algorithms can be regarded as the first step toward this aim and more complex algorithms could be incorporated using e.g. adaptive neuro-fuzzy inference systems. This finally points to future hybrid systems that should combine automated learning with knowledge representation capabilities (Chlingaryan et al., 2018). It remains to be expected that more involvement of experts in defining the system behavior will contribute to greater acceptance and increased engagement with VRNA systems, especially if it is recognized as a powerful tool to increase operational efficiency and comply with increasingly stringent legal requirements.

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Summary

The principle of site-specific mineral nitrogen (N) fertilization to adjust dose rates to the spatially varying needs of the crop has been studied for many years and has proven the potential to achieve economic and ecological advantages compared to uniform application. However, its widespread establishment has failed primarily because the used agronomic algorithms can represent the complexity of N management only to a limited extent. Due to inherent temporal and spatial dynamics, this requires an ever-new adapted interpretation of different parameters relevant for plant growth against the background of specific local conditions before each N application. In addition, the current application technology is affected by significant limitations concerning the precise realization of the site-specific fertilization strategy.

The overarching aim of this cumulative dissertation was to develop an integrated technical approach to define and implement situational and multi-parametric site-specific fertilization strategies with the aid of agronomic expert knowledge. The following main aspects were investigated: (1) elaboration and analysis of a methodology to imitate the agronomic algorithms of an established real-time fertilization system in a fuzzy system and to extend it to a multi-parametric expert system, (2) development, integration and technical verification of a real-time control system for multiple data fusion based on the fuzzy expert system, as well as spatial synchronization of dose rate determination and realization, (3) conceptualization of a consistently digital process chain to facilitate decision making, data management and execution in the field, and its evaluation via a prototypic implementation.

This work represents the first systematic attempt to explicitly define the cause-effect relationships for a site-specific N application based on expert knowledge of farmers or agronomic advisors and to transfer them into a machine-readable algorithm. The model of a connection of crop N uptake information (SN) provided by a Yara N-Sensor ALS2 with mapped soil apparent electrical conductivity (ECa) was applied during all phases. This was representative for a fusion of real-time and map-based information, which is of high practical relevance. At the same time, it places comparatively high demands on the technical implementation and thus covers most of the challenges that have to be solved also for other constellations of data sources, as well as sensor and application technologies.

With knowledge about their basic behavior, as well as a comprehensive data acquisition under different conditions, the agronomic algorithms of the N-Sensor were modeled and validated for specific use cases in a fuzzy system, where after simulations compared to the original data, the Pearson correlation coefficient was always above 99% and the percentage root mean square error did

not exceed 0.14%. Via this model, the N-sensor algorithms were transformed into a form adapted to human cognition and reasoning in order to be intuitively adapted by the user and linked to other parameters. Simulation studies on a fusion with the ECa under specific assumptions regarding the weather-dependent availability of water suggested that a multi-parametric system results in more robust decisions.

The real-time fusion of SN and ECa data was implemented via a control algorithm that had the inference mechanisms of the previously developed fuzzy expert system incorporated. In addition, it included a model to compensate technical latencies in the application system and provided dynamic synchronization of georeferenced dose rate determination and fertilizer application via an odometric approach, whereby a differentiation according to sections was made. A system verification, which was conducted under different travel speed scenarios after the embedment in a real sensor-tractor-spreader system, implied a high reliability of the control system. Deviations from ideal synchronization did not exceed 1.5 m in any case and exceeded 1 m in only 2.3% of the cases in the worst data set, which is a sufficient accuracy from a practical point of view. The distinction of dose rates was made solely based on the ECa and therefore resulted in only minor differences between the sections.

In particular, due to the specific challenges arising from the strong user-centeredness, a system architecture for a web-based, digital process chain was designed, which included all sub-processes necessary for site-specific N management, such as system configuration via suitable user interfaces, automated data management, execution in the field and documentation. By considering different scenarios in terms of used data or sensor and application technologies, respectively, the concept was validated as consistent. The potentials and limitations, as well as specific requirements regarding the technical realization were clarified in a prototypical implementation. The generic properties of the overall concept allow it to be supplemented by established approaches and can in turn strengthen them with the functional integration of expert knowledge.

Zusammenfassung

Das Prinzip der teilflächenspezifischen mineralischen Stickstoff (N) -Düngung zur Anpassung der Düngermengen an den kleinräumig variierenden Bedarf der Kultur wird seit vielen Jahren untersucht und hat nachweislich das Potenzial zur Erzielung ökonomischer und ökologischer Vorteile gegenüber einer flächeneinheitlichen Ausbringung. Allerdings scheitert dessen breite Etablierung vor Allem daran, dass die verwendeten agronomischen Algorithmen die Komplexität des N Managements nur in begrenztem Maße abbilden können. Aufgrund inhärenter zeitlicher und räumlicher Dynamiken erfordert diese vor jeder Gabe eine neu angepasste Interpretation von unterschiedlichen, für das Pflanzenwachstum relevanten Parametern vor dem Hintergrund spezifischer, lokaler Begebenheiten. Darüber hinaus ergeben sich bei der heute gängigen Applikationstechnik signifikante Einschränkungen in der präzisen Realisierung der teilflächenspezifischen Düngestrategie.

Übergeordnetes Ziel dieser kumulativen Dissertation war die Entwicklung eines ganzheitlichen technischen Ansatzes, um mithilfe von agronomischem Expertenwissen situative und mehrparametrische, teilflächenspezifische Düngestrategien festzulegen und zu realisieren. Dabei wurden im Wesentlichen folgende Teilaspekte untersucht: (1) Erarbeitung und Analyse einer Methodik, um die agronomischen Algorithmen eines etablierten Echtzeit-Düngesystems in einem Fuzzy System zu imitieren und dieses zu einem mehrparametrischen Expertensystem zu erweitern, (2) Entwicklung, Integration und technische Verifizierung einer Echtzeitsteuerung für die multiple Datenfusion basierend auf dem Fuzzy Expertensystem und die räumliche Synchronisierung von Dosiermengenvorgabe und –realisierung, (3) Konzeptionierung einer durchgängig digitalen Prozesskette zur Vereinfachung von Entscheidungsfindung, Datenmanagement und Ausführung auf dem Feld, sowie deren Evaluierung über eine prototypische Implementierung.

Dieser Arbeit liegt der erstmalige systematische Versuch zugrunde, die Wirkzusammenhänge für eine teilflächenspezifische Düngegabe explizit auf der Basis von Expertenwissen von Landwirten oder agronomischen Beratern zu definieren und sie in einen maschinenlesbaren Algorithmus zu überführen. Dabei wurde in allen Phasen das Modell einer Verknüpfung der von einem Yara N-Sensor ALS2 bereitgestellten Information über die N-Aufnahme des Bestandes (SN) mit der kartierten scheinbaren elektrischen Leitfähigkeit des Bodens (ECa) angewendet. Dieses war repräsentativ für eine Fusion von Echtzeit- und kartenbasierter Information, welche von hoher praktischer Relevanz ist. Gleichzeitig stellt es vergleichsweise hohe Anforderungen an die technische Umsetzung und deckt somit die meisten Herausforderungen ab, die auch bei anderen Konstellationen an Datenquellen, sowie Sensor- und Applikationstechnologien gelöst werden müssen.

Mithilfe von Kenntnis über deren grundlegendes Verhalten sowie umfassenden Datenerhebungen unter unterschiedlichen Bedingungen wurden die agronomischen Algorithmen des N-Sensors für einen bestimmten Anwendungsbereich in einem Fuzzy System modelliert und validiert, wobei nach Simulationen im Vergleich zu den originären Daten der Korrelationskoeffizient stets über 99% lag und der prozentuale mittlere quadratische Fehler 0.14% nicht überschritt. Über dieses Modell wurden die N-Sensor Algorithmen in eine an die menschliche Kognition und Schlussfolgerung angepasste Form überführt, um durch den Nutzer intuitiv angepasst und mit weiteren Parametern verknüpft werden zu können. Simulationsstudien zu einer Fusion mit der ECa unter spezifischen Annahmen bezüglich der wetterabhängigen Verfügbarkeit von Wasser ließen den Schluss zu, dass ein mehrparametrisches System zu robusteren Entscheidungen führt.

Die Echtzeit-Fusion von SN- und ECa-Daten wurde über einen Steuerungsalgorithmus, der über die Inferenzmechanismen des zuvor entwickelten Fuzzy Expertensystems verfügte, implementiert. Darüber hinaus beinhaltete dieser ein Modell zur Kompensation von technischen Latenzen im Applikationssystem und sorgte über einen odometrischen Ansatz für eine nach Teilbreiten differenzierte, dynamische Synchronisation von georeferenzierter Dosiermengendefinition und Düngerapplikation. Die nach der Einbettung in ein reelles Sensor-Traktor-Streuer System durchgeführte Systemverifikation unter verschiedenen Fahrgeschwindigkeits-Szenarien ließ auf eine hohe Zuverlässigkeit der Steuerung schließen. Die Abweichungen von einer idealen Synchronisation überschritten in keinem Fall 1,5 m und lagen im schlechtesten Datensatz in nur 2,3% der Fälle über 1 m, was eine aus praktischer Sicht ausreichende Genauigkeit darstellt. Die Unterscheidung von zwei Dosiermengen erfolgte allein in Abhängigkeit der ECa und führte daher nur zu geringen Unterschieden zwischen den Teilbreiten.

Insbesondere aufgrund der speziellen Herausforderungen, die sich aus der starken Nutzerzentriertheit ergaben, wurde eine Systemarchitektur für eine web-basierte, digitale Prozesskette konzipiert, welche alle für das teilflächenspezifische N Management notwendigen Teilprozesse, wie die Systemkonfiguration über geeignete Nutzerschnittstellen, das automatisierte Datenmanagement, die Ausführung auf dem Feld und die Dokumentation umfasst. Mit der Betrachtung unterschiedlicher Szenarien hinsichtlich verwendeter Daten bzw. Sensor- und Applikationstechnologien wurde das Konzept als konsistent validiert. Die Potenziale und Einschränkungen, sowie spezifische Anforderungen hinsichtlich der technischen Umsetzung wurden in einer prototypischen Implementierung verdeutlicht. Die generischen Eigenschaften des Gesamtkonzepts erlauben eine Ergänzung um etablierte Ansätze und können diese wiederum durch die funktionale Einbindung von Expertenwissen stärken.

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