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Dissertation

Alexander Steiger

Spatial Data Infrastructure and Algorithms for Variable Rate Fertigation in Precision Agriculture

PROFESSUR

Geodäsie und
Geoinformatik

Universität
Rostock



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Universität
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ROSTOCK UNIVERSITY

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SCIENCES

Doctoral Thesis

Spatial Data Infrastructure and Algorithms for Variable Rate Fertigation in Precision Agriculture

Dissertation to obtain the doctoral degree of
Doktor der Ingenieurwissenschaften (Dr.-Ing.)

at the

**Faculty of Agriculture, Construction and Environmental
Sciences**

of the **Rostock University**

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Abstract

The increasing pressure on agriculture to increase productivity and ensure food security, while at the same time reducing environmental impacts, requires a more efficient use of water and nutrients. Precision Agriculture (PA) addresses this challenge through site-specific management, where inputs are applied according to the spatial and temporal variability of soil, crop, and environmental conditions. This dissertation investigates the development of algorithms and a spatial data infrastructure (SDI) for information-driven irrigation and fertilization, also known as Variable Rate Fertilization (VRFI). The research was conducted within the framework of the European ICT-AGRI-FOOD project *ADDFerti*, which aimed to design and validate a fully automated ICT platform for site-specific fertilization in arable farming.

A key outcome of this work is the design and implementation of a cloud-based SDI, realized through an open-source GeoNode environment that integrates sensor data, spatial layers, and decision-support outputs within a standardized OGC/ISO framework. Multiple data sources were connected to the SDI – including in-field LoRaWAN soil moisture sensors, weather services, and high-resolution soil and crop maps – to provide seamless interfaces for data transfer between the Decision Support System (DSS) and the field machinery. Algorithms were developed for irrigation and fertilizer rate calculation, and the automated generation of site-specific application maps. These methods were implemented in a Python-based DSS located in the cloud, capable of running fully automatically, producing fertilization maps within seconds, and publishing them directly to the geoportal for retrieval by the Hose-Reel Irrigation System (HIS).

The ICT system (consisting of the sensor network, SDI, and DSS for creating application maps) was deployed during field experiments at the *ADDFerti* test sites in Germany, France, and Turkey. In the final experiment in Turkey, the integrated solution was successfully operated in a real-world fertilization event using the modified HIS, proving its feasibility under real-world conditions.

The results show that the developed system can automatically combine sensor data, weather information, and soil and crop maps within a standardized SDI to create fertilization application maps that can be directly used by field machinery. The approach provides a practical pathway for implementing variable-rate fertilization in arable farming and demonstrates how open-source geospatial tools and open standards can make advanced precision farming technologies accessible to farmers and researchers alike.

Zusammenfassung

Der zunehmende Druck auf die Landwirtschaft, die Produktivität und Ernährungssicherheit zu erhöhen und gleichzeitig Umweltbelastungen zu reduzieren, erfordert einen effizienteren Einsatz von Wasser und Nährstoffen. Die Präzisionslandwirtschaft (Precision Agriculture, PA) begegnet dieser Herausforderung durch das Prinzip der teilflächenspezifischen Bewirtschaftung, bei der landwirtschaftliche Inputs entsprechend der räumlichen und zeitlichen Variabilität von Boden-, Pflanzen- und Umweltbedingungen ausgebracht werden. Diese Dissertation untersucht die Entwicklung von Algorithmen und einer Geodateninfrastruktur (Spatial Data Infrastructure, SDI) für informationsgetriebene Bewässerung und Düngung, auch bekannt als Variable Rate Fertigation (VRFI). Die Arbeiten wurden im Rahmen des europäischen ICT-AGRI-FOOD-Projekts *ADDFerti* durchgeführt, dessen Ziel die Entwicklung und Validierung einer vollständig automatisierten ICT-Plattform für teilflächenspezifische Fertigation im Ackerbau war.

Ein zentrales Ergebnis dieser Arbeit ist die Konzeption und Implementierung einer cloudbasierten SDI, die in einer Open-Source-GeoNode-Umgebung realisiert wurde, welche Sensordaten, räumliche Datensätze und Ergebnisse der Entscheidungsunterstützung innerhalb eines standardisierten OGC/ISO-Rahmens zusammenführt. Über diese SDI wurden in situ LoRaWAN-Bodenfeuchtesensoren, Wetterdienste sowie hochauflösende Boden- und Pflanzenkarten angebunden, wodurch eine nahtlose Datenübertragung zwischen Decision Support System (DSS) und Feldtechnik ermöglicht wurde. Die entwickelten Algorithmen zur Berechnung von Bewässerungs- und Düngemengen wurden in einem cloudbasierten, Python-gestützten DSS implementiert, das vollautomatisch arbeitet und teilflächenspezifische Applikationskarten innerhalb weniger Sekunden erzeugt und veröffentlicht.

Das ICT-System (bestehend aus Sensornetzwerk, SDI und DSS) wurde in Feldversuchen an den *ADDFerti*-Versuchsstandorten in Deutschland, Frankreich und der Türkei eingesetzt und im abschließenden Experiment in der Türkei erfolgreich unter Praxisbedingungen mit einem modifizierten Schlauchwagen-Bewässerungssystem betrieben.

Die Ergebnisse zeigen, dass das entwickelte System Sensordaten, Wetterinformationen sowie Boden- und Pflanzenkarten innerhalb einer standardisierten SDI automatisch verknüpfen und daraus direkt maschinenlesbare Fertigungs-Applikationskarten erzeugen kann. Der vorgestellte Ansatz bietet einen praxisnahen Weg zur Umsetzung von VRFI im Ackerbau und verdeutlicht das Potenzial offener Standards und Open-Source-Geowerkzeuge für zukünftige datengetriebene Bewässerungs- und Düngesysteme.

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List of Abbreviations

API	Application Programming Interface
CSW	Catalog Service for the Web
DSS	Decision Support System
FTP	File Transfer Protocol
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GUI	Grafical User Interface
IoT	Internet of Things
ISO	International Organization for Standardization
ICT	Information and Communication Technology
LoRaWAN	Long Range Wide Area Network
LPWAN	Low Power Wide Area Network
MZ	Management Zones
OGC	Open Geospatial Consortium
PA	Precision Agriculture
SDI	Spatial Data Infrastructure
SOS	Sensor Observation Service
SWE	Sensor Web Enablement
UAV	Unmanned Aerial Vehicle
UR	Uniform Rate VR
Variable Rate	
VRF	Variable Rate Fertilization
VRFI	Variable Rate Fertilization & Irrigation (fertigation)
VRI	Variable Rate Irrigation
WCS	Web Coverage Service
WFS	Web Feature Service
WMS	Web Map Service

Chapter 1

Introduction

Precision agriculture (PA) emerged in the mid-1980s (Robert, 2002) and has since become a cornerstone of modern farming practices. PA aims to optimize the management of farm inputs such as fertilizers, herbicides, seeds, and fuel used in tillage, planting, and spraying operations. It is based on the principle of applying inputs at the right time, in the right amount, and at the right place. In agronomic literature, this concept is often extended to the “5R” framework, which also includes the right input or source and the right application method.

Rather than treating fields as uniform blocks, PA recognizes spatial and temporal variability and divides them into management zones based on soil and crop characteristics, topography, and management history. By enabling site-specific crop management, it improves productivity and farm profitability while contributing to environmental protection and the long-term sustainability and resilience of agricultural production (Gebbers and Adamchuk, 2010; Mulla, 2013; Noack, 2025).

The practical application of PA has been made possible by the convergence of several key technologies: Global Navigation Satellite Systems (GNSS) for precise positioning, Geographic Information Systems (GIS) for spatial data integration and analysis together with initiatives pushing open standards for data interoperability, remote and proximal sensing for soil and crop monitoring, on-the-go yield and soil sensors, and Farm Management Information Systems (FMIS) for decision support and operational management (Stafford, 2000; Nash et al., 2009).

Recent advancements in technologies such as the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), cloud computing, remote sensing, and robotics have significantly enhanced the efficiency of agricultural operations. This digital transformation of agriculture is often described as the fourth agricultural revolution, or Agriculture 4.0, which is paving the way for smarter, more efficient, and environmentally sustainable farming practices (Javaid et al., 2022).

In practice, PA follows a cycle of agricultural operations throughout the crop growth period, a typical cropping cycle with integrated PA practices is shown in Fig. 1.1. This begins with soil preparation and sowing, continues during plant growth with fertilization and crop protection, and culminates in harvest. Beyond the variable rate (VR) applications themselves, PA practices can be integrated at nearly every stage of this cycle through continuous data

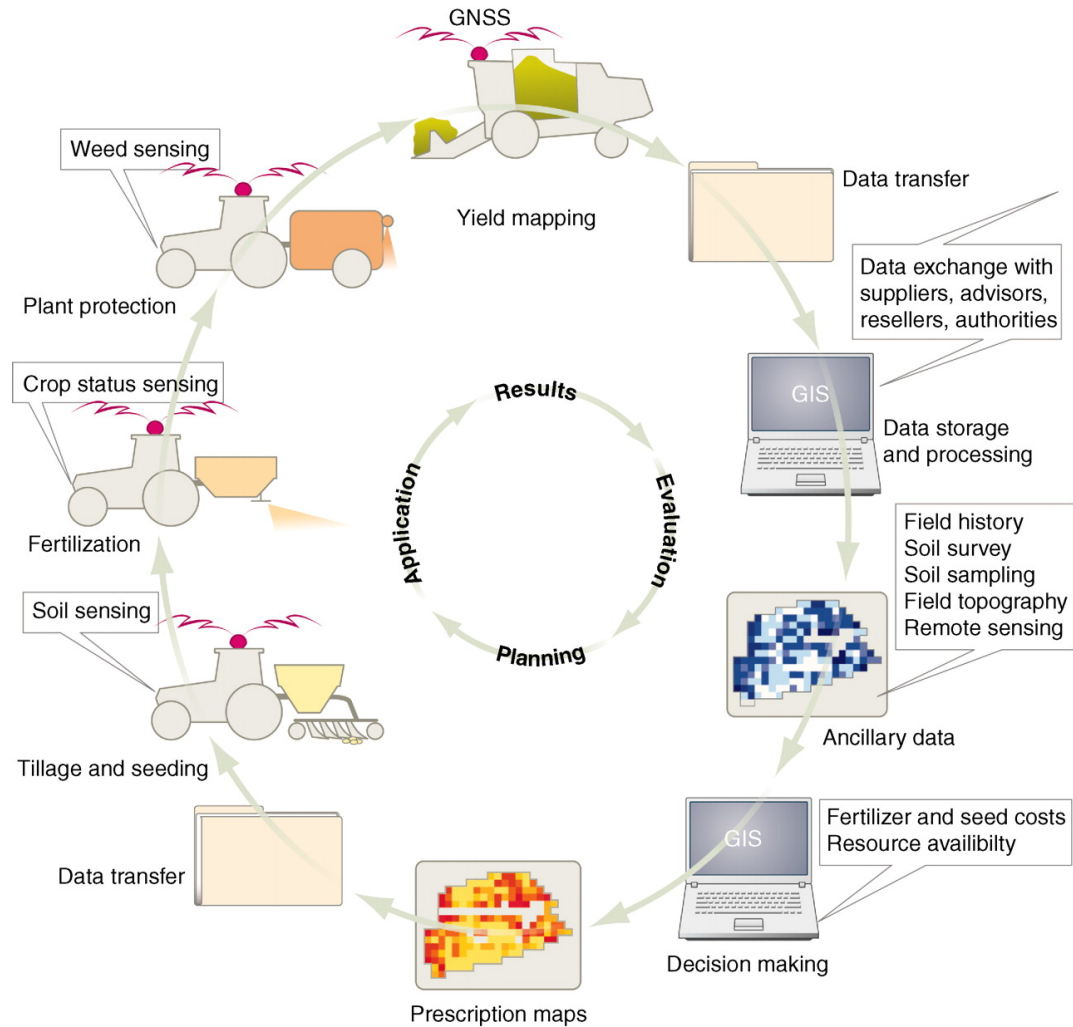


FIGURE 1.1: Cycle of precision agriculture. Source: Gebbers (2018).

collection, processing, analysis and finally planning, and decision-making, typically within a GIS or FMIS environment (Shafi et al., 2019; Bill et al., 2022). In general, PA strategies can be classified as either map-based or sensor-based. Map-based approaches, also called predictive approaches, use historical and spatial data to forecast crop needs, which is then applied based on a GNSS receiver and a prescription map. Sensor-based, or reactive approaches, adjust input rates in real time based on actual soil or crop status, requiring live sensing and on-the-go data processing (Gebbers and Adamchuk, 2010; Al-Gaadi et al., 2023).

An important subset of PA is the site-specific management of irrigation and fertilization. Both practices strongly influence crop growth and resource efficiency, and their success or failure can have tremendous consequences for farm productivity and environmental sustainability. When the supply of water and nutrients is combined into a single operation, the practice is referred to as fertigation, which offers distinct advantages in terms of efficiency and sustainability.

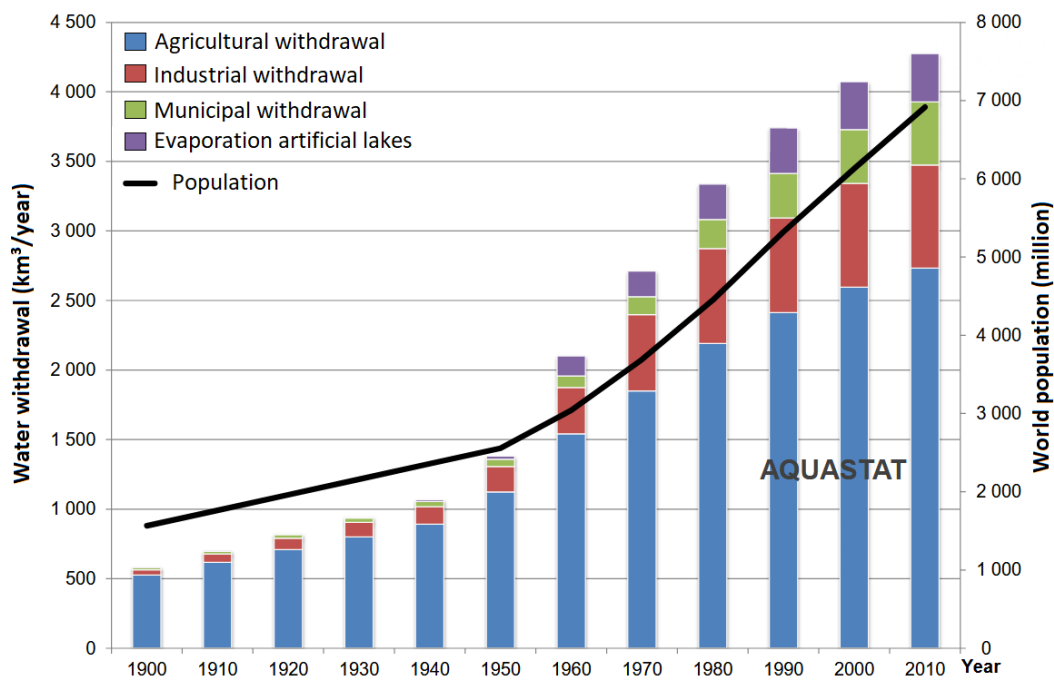


FIGURE 1.2: Global population and water withdrawal between 1900 and 2012.
Source: FAO (2024), modified.

1.1 Motivation

Irrigation

Irrigation has played a decisive role in agricultural production for thousands of years and continues to contribute substantially to global food security. Today, one third of the world's food is produced on 21 % of cultivated land that is irrigated (Eisenhauer et al., 2021). Irrigation has enabled crop production in otherwise arid and semi-arid regions, such as the Nile Valley in Egypt or the Mesopotamian Plain between the Euphrates and Tigris, which without artificial water supply would yield little to no food. Globally, around 70 % of freshwater withdrawals are used for agriculture, and absolute withdrawal rates have risen steadily over the past century in parallel with population growth (see Figure 1.2).

Besides the overall increase in water withdrawals, climate change is altering rainfall patterns and intensifying drought risk. Projections indicate that more than 80 % of global croplands will face growing water limitations in the future (Liu et al., 2022). As a regional example, an analysis of precipitation trends in Bavaria between 1961 and 2010 showed a significant decline in April rainfall across most districts, with reductions ranging from –10 % to –33 % (Nowak, 2021). In Germany, the irrigated area has already expanded from 372,000 ha in 2009 to 554,000 ha in 2022 (Destatis, 2023). Similar trends can be observed across Europe, where supplemental irrigation is becoming increasingly important even in regions that historically relied on rainfall alone.

(Hamidov et al., 2018; Peltonen-Sainio et al., 2021). In southern Europe, where agriculture is already highly dependent on irrigation, projections suggest yield reductions of up to 10 % for irrigated grain maize under a 2 °C warming scenario, primarily due to water scarcity (Peltonen-Sainio et al., 2021).

Traditional irrigation methods often fail to align water supply with actual plant demand. Uniform rate (UR) applications not only waste water, nutrients, and energy, but also contribute to soil degradation through waterlogging, erosion, and salinization (Eisenhauer et al., 2021).

Fertilization

Nitrogen (N) and Phosphorus (P) are generally the most limiting nutrients in crop production. However, both under- and over-application of fertilizers can result in substantial agronomic and environmental risks. Under-fertilization can reduce yields and crop quality, while over-fertilization not only leads to unnecessary economic costs but also contributes to environmental degradation.

The risks associated with N fertilizers are well documented. Nearly half of applied N is not taken up by crops but instead lost to the environment through volatilization, surface runoff, and leaching (Martínez-Dalmau et al., 2021). This unassimilated N frequently migrates into groundwater in the form of nitrate (NO_3^-), contributing to the pollution of aquatic ecosystems and drinking water sources. In addition, N emissions into the atmosphere exacerbate air quality problems and contribute to climate change (Martínez-Dalmau et al., 2021). Inefficient N use not only damages ecosystems but also poses direct risks to human health, including increased incidences of cancer, cardiovascular disease, and asthma (Townsend et al., 2003; de Vries, Wim, 2021). Without mitigation, world wide reactive nitrogen (Nr) pollution is expected to rise substantially, with projections indicating an increase of 102-156 % by 2050 compared to 2010 levels, of which agriculture being the largest contributor (Bodirsky et al., 2014). Excessive N fertilization can also be detrimental to crop yield, as it may cause premature ripening and excessive vegetative growth (Wang et al., 2011; Albornoz, 2016).

Phosphorus is a non-renewable resource mined from phosphate rock, with current reserves projected to be depleted by around 2300 (Daneshgar et al., 2018). The main environmental concern associated with P is its transfer from agricultural soils to surface waters, as even very small concentrations are sufficient to trigger eutrophication (Hart et al., 2004).

As response to fertilizer pollution from agriculture, the European Union has launched the Farm to Fork (F2F) strategy in 2020 as part of the European Green Deal. This program aims to transform the agri-food system into a more sustainable one, with one of the target aiming at a 20 % reduction in chemical fertilizer use and a 50 % reduction in nutrient loss by 2030, while preserving soil fertility (European Commission, 2020; Kagan et al., 2024). Preceding this, in 2008 the EU Nitrates Directive 91/676/EEC set a maximum threshold of 50 mg/l nitrate in groundwater (European Council, 2008). In Germany,

however, 26.6 % of monitoring points still exceeded this value between 2020 and 2022 (BMU, 2024).

Variable Rate for Efficient Water and Nutrient Use

Technological solutions are needed to increase input use efficiency. Variable rate irrigation (VRI) has been shown to increase yields while reducing water use (O'Shaughnessy et al., 2019; Evett et al., 2020). Similarly, variable rate fertilization (VRF) can enhance productivity while significantly reducing fertilizer inputs and environmental impacts (Basso et al., 2016; Guerrero and Mouazen, 2021).

Variable rate fertigation (VRFI) integrates VRI and VRF into a single process. A key advantage of fertigation is its ability to increase nutrient recovery efficiency, as fertilizer applications can be split into smaller doses aligned with crop uptake dynamics (Incrocci et al., 2017). VRFI has been shown to achieve higher yields while simultaneously reducing both water and fertilizer use (Sharma and Irmak, 2020).

In recent years, commercial solutions for VRI and VRF have become increasingly available, with adoption rates steadily rising (Nowak, 2021; Evett et al., 2020). By contrast, VRFI systems for arable farming remain largely in the research and development stage, as operational complexity and equipment costs currently limit their economic feasibility (Sharma and Irmak, 2020). Developing VRFI systems for practical farm use requires novel approaches that integrate sensor networks, spatial data infrastructures, and decision support algorithms with field application equipment. This dissertation addresses this need by focusing on the development of algorithms and data infrastructures for information-driven fertigation, with particular emphasis on the preparation of site-specific application maps and their deployment in VRFI systems.

1.2 Aim of this dissertation

The overarching aim of this dissertation is to develop algorithms and a spatial data infrastructure for information-driven fertilization and irrigation in precision agriculture.

The following **objectives** are pursued:

1. Design and implement a spatial data infrastructure capable of integrating heterogeneous agricultural data sources.
2. Develop algorithms for generating VRFI recommendations.
3. Integrate sensor data, spatial datasets, and modelling outputs into an automated decision-support workflow.
4. Validate the developed system through real-world field experiments within the ADDFerti project.

To achieve these objectives, the following **research questions** need to be addressed:

1. Which irrigation systems are technically and economically suitable for adaptation to VRFI in large-scale arable farming?
2. What types of data and sensing solutions are required to monitor soil, crop, and environmental conditions relevant for VRFI?
3. Which methodological approaches and DSS algorithms are suitable for generating reliable site-specific fertigation recommendations?
4. What are the requirements for an SDI to support automated data flows and to integrate sensing, spatial data management, DSS logic, and field application into a coherent VRFI workflow?

1.3 Structure of the Thesis

The thesis is organized into nine chapters. Chapter 1 introduces the motivation, research objectives, and overall structure of the work. Chapter 2 provides a review of the state of the art in VR irrigation and fertilization technologies, with a particular focus on application equipment, sensing solutions, spatial data infrastructures, and decision support systems. Chapter 3 presents the ADDFerti project, which provided the as the central framework for this research, as well as the description of the experimental test sites in Germany, France, and Turkey.

Chapters 4 and 5 describe the sensor technologies and the spatial data infrastructure developed and deployed within ADDFerti. Chapter 6 details the design and implementation of the automatic DSS for fertigation, including the algorithms for management zone delineation and application map generation. Chapter 7 presents the results of the integrated solution in a case study conducted in Turkey. Chapter 8 discusses the key findings and the technical and conceptual implications of the work, and it outlines opportunities for further research. Finally, Chapter 9 provides a summary and concludes the thesis.

Chapter 2

State of the Art in Application Equipment, Sensing, Geodata Infrastructures, and Decision Support Systems for Information-Driven Fertilization and Irrigation

The ongoing advancements in PA are driven by a wide range of innovative technologies. Central among these are VRI, VRF, and their combination as VRFI, which enable the site-specific adjustment of water and nutrient inputs. By aligning applications with actual field conditions, these technologies can improve resource use efficiency, reduce environmental impacts, and support higher and more sustainable yields. This chapter provides an overview of the core technologies and methodological approaches that underpin VRFI, including application equipment, sensor systems for soil and crop characterization, spatial data management, and decision support algorithms.

2.1 Fertigation Application Equipment in Precision Agriculture

Fertigation refers to the application of dissolved fertilizers through an irrigation system. The practical implementation of VRFI depends primarily on the availability of suitable field equipment. In arable farming, three main irrigation concepts are commonly employed: surface irrigation, stationary systems such as drip and fixed sprinkler irrigation, and traveling systems like hose reels, center pivots, and lateral-move systems (Eisenhauer et al., 2021). With the exception of surface irrigation, most of these systems are, to varying degrees, suitable for modification to enable VRFI.

This section provides an overview of the main types of irrigation systems relevant for VRFI in arable farming, with a focus on their technical configuration, adaptability for VR control, and current levels of adoption in both commercial and research settings.

From an engineering point of view, VRI can be achieved using various control mechanisms, including speed control, sectional valve control, and individual nozzle or emitter control (O'Shaughnessy and Rush, 2014). In traveling irrigation systems such as hose-reels, center pivots, or lateral-move systems, the most commonly applied strategy is speed modulation which is relatively easy to retrofit onto existing equipment. Transitioning from VRI to VRFI introduces an additional level of complexity, as it requires independent regulation of water and nutrient application. This is typically achieved through the integration of controlled injection systems that deliver fertilizer into the irrigation flow, either into the irrigation system as a whole or per section. However section-controlled VRFI systems remain largely confined to research environments or high-end commercial platforms due to their technical and economic complexity.

Three principal operational strategies can be distinguished for VR application systems: map-based, sensor-based and map-sensor-based approaches (Zhang et al., 2002; Bill et al., 2022). Map-based systems rely on pre-generated application maps that are uploaded to the machine's control terminal prior to field operations. These maps are typically derived from heterogeneous data sources such as historical yield data, remote sensing imagery, and soil analyses; the methodology behind their creation is described in Section 2.2. In contrast, sensor-based systems determine input rates dynamically during (or immediately before) field operations by responding to real-time data from onboard or stationary sensors monitoring soil or crop status. Onboard sensors are well-established in fertilizer spreaders (e.g., the Yara N-Sensor), but have not yet been applied in VRI or VRFI systems. Stationary sensors, particularly for soil moisture monitoring, are more commonly used in irrigation management. Map- and sensor-based approaches can also be combined in a hybrid strategy, where real-time sensor data is used to refine pre-generated maps (Bill et al., 2022). While this method offers high spatial and temporal precision, it requires a functional DSS to integrate and interpret the data streams effectively.

PA relies on several key technologies, including GNSS-based positioning, flow control components, precision flow meters, and standardized data interfaces. A central standard for ensuring interoperability in PA is ISO 11783, commonly known as ISOBUS. It defines a wired serial communication network for tractors and implements, enabling seamless data exchange between terminals, sensors, actuators, and FMISs—regardless of manufacturer. The standard covers connector specifications, communication protocols, network architecture, and user interface design. In addition to its native file format (ISOXML), ISOBUS also supports the use of Shapefiles for application maps (International Organization for Standardization, 2017; Noack et al., 2024). For irrigation systems, so far, ISOBUS is not used, as these systems typically rely on manufacturer-specific proprietary control platforms (e.g., Lindsay FieldNET¹,

¹FieldNET: <https://www.lindsay.com/euas/en/irrigation/brands/fieldnet>

Valley ICON², Reinke ReinCloud³). However, from a future perspective, integrating irrigation systems into the ISOBUS framework would enhance interoperability and enable seamless integration of VRI and VRFI operations into FMISs.

A broad range of irrigation systems is used in agricultural practice, each suited to specific field geometries, water availability, and operational scales. For VRFI applications, the most relevant system types are drip irrigation, center pivot and lateral-move systems, as well as hose-reel based irrigation platforms.

2.1.1 Drip Irrigation Systems

Drip irrigation (also called micro-irrigation), is a stationary system that delivers water directly to the root zone via a network of pipes, emitters, and valves. Simpler configurations use perforated hoses to distribute water along crop rows, whereas more sophisticated systems employ specialized emitters (drippers, micro-sprinklers), with the option for manual flow adjustment and pressure-compensation.

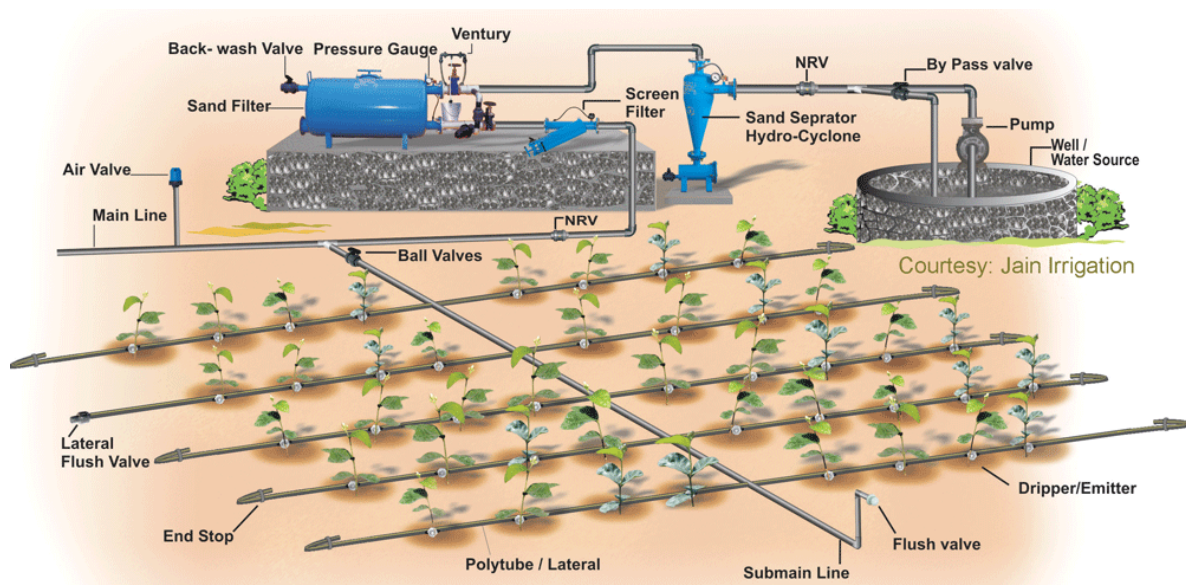


FIGURE 2.1: Schematic layout of a pressurized drip irrigation system, showing the filtration, pumping, and distribution components, as well as a configuration of submain lines, laterals, and emitters. Source: Jisl, Public Domain, via Wikimedia Commons.

Drip irrigation is predominantly used for high-value crops, orchards, vineyards, and greenhouse production due to its high water-use efficiency and suitability for UR fertigation. Water is applied at low pressure and in small volumes, thereby minimizing losses from evaporation and deep percolation. Drip irrigation can also be installed sub-surface at a depth between 20 and 50 cm, further enhancing water-use efficiency.

²ICON: <https://valleyirrigation.com/ICON>

³ReinCloud: <https://reinke.com/reincloud>

Implementing fine-grained VRI or VRFI in drip irrigation systems is economically challenging. This applies already to sectional control and becomes even more costly for emitter-level control. For example, assuming a row spacing of 1 m and emitters placed every 0.5 m along each row, a single hectare (100 m × 100 m) would require approximately 20 000 individual emitters:

$$\begin{aligned} 100 \text{ m} / 1 \text{ m} &= 100 \text{ rows,} \\ 100 \text{ m} / 0.5 \text{ m} &= 200 \text{ emitters per row,} \\ 100 \text{ rows} \times 200 \text{ emitters} &= 20\,000 \text{ emitters per hectare.} \end{aligned}$$

The installation, maintenance, and control infrastructure required for individual emitter regulation at this density make fine-scale VRFI economically not viable in most scenarios.

VR drip irrigation is still a topic of research, with most studies focusing on irrigation scheduling and manually setting emitter or sectional flow rates at the beginning of the season (Barkunan et al., 2019; Ortuani et al., 2019). Highlighted can be the work of AL-agele et al. (2021), who designed a relatively low-cost emitter (9 €) that uses drop counting to control water application rates.

2.1.2 Stationary Sprinkler Irrigation

Stationary sprinkler systems distribute water through a fixed network of pipes and sprinklers that are permanently or semi-permanently installed in the field. Water is applied under moderate to high pressure, creating an artificial rainfall pattern with relatively uniform distribution.

Stationary sprinkler systems are typically used for vegetables and other high-value field crops that require frequent and well-controlled irrigation. Compared to travelling systems, their installation cost per hectare is higher, and the fixed layout may restrict machinery access and reduce operational flexibility during field work.

Adapting stationary sprinkler systems for VRI or VRFI faces similar constraints as drip irrigation. Although technically feasible, the required investment and system complexity make such adaptations economically impractical with current technology.

2.1.3 Center Pivot and Lateral-Move Systems

Center pivot and lateral-move systems are semi-mobile sprinkler irrigation platforms that move continuously across the field, irrigating in circular (pivot) or linear (lateral-move) patterns. They are especially suited for large-scale arable production due to their scalability, automation potential, and economic efficiency. In 2017 85% of sprinkler-irrigated land in the U.S. was under center pivot irrigation (Perdue and Hamer, 2019).

VRI in these systems can be achieved through speed modulation, sectional control via solenoid valves, or individual sprinkler control using pulse-width modulation (PWM). Commercial VRI solutions have been available since the early 2000s (Vellidis et al., 2016), with several manufacturers now offering fully integrated VRI platforms (e.g. Zimmatic Precision VRI⁴, Valley VRI iS⁵).

Implementing VRFI requires additional infrastructure for nutrient injection, typically consisting of pressurized fertilizer tanks or unpressurized reservoirs equipped with dosing pumps. In advanced configurations, fertilizer flow can be regulated independently of water flow and at the level of individual irrigation sections.

Williams et al. (2018) retrofitted a lateral-move irrigation system to enable section-controlled VR nitrogen fertigation independently from water flow. The system used a 1250 L nitrogen supply connected to a 114 L pressurized bladder tank, feeding a main nitrogen line along the boom. Nitrogen was injected via ten 24-volt solenoid valves into sections of 7 m width, corresponding to four nozzles per section.

Sobenko et al. (2018) developed a novel VR sprinkler, by combining a orifice sprinkler mechanism with a Arduino and a stepper-motor for real-time flow rate control.

Although commercial VRI systems are well established and increasingly adopted, section-controlled VRFI remains rare in practice due to higher costs, greater technical complexity, and limited availability outside research contexts. Early experiments, such as those by Camp et al. (1998), demonstrated that it is technically possible to implement section-controlled VRFI in center-pivot systems; however, large-scale commercial implementations remain uncommon.

2.1.4 Hose reel irrigation systems (HIS)

HIS are mobile sprinkler platforms that irrigate fields by retracting a large-diameter polyethylene hose attached to a boom or high-pressure rain gun mounted on a cart. The system is deployed by unspooling the hose with a tractor along a tramline; irrigation is carried out as the reel retracts slowly, driven by a water-powered turbine mechanism that converts hydraulic energy into rotational motion. HIS are available in various sizes, with hose lengths of up to 900 m and boom working widths of up to 95 m (RM Irrigation, 2025). Their main advantage lies in their flexibility, making them particularly well suited for irregular field shapes, smaller field sizes, or production systems where permanent installations are not required. VR applications are only practical in boom configurations, as rain guns lack the precision and uniformity required for site-specific application.

⁴Zimmatic Precision VRI: <https://www.lindsay.com/euas/en/irrigation/brands/zimmatic/products/precision-irrigation/>

⁵Valley VRI iS: <https://www.valleyirrigation.com/vri-is>



FIGURE 2.2: Hose reel irrigation system with boom configuration (left), with manually programmable speed control unit (right) from the manufacturer RM. Source: RM Irrigation (2025).

VRI in hose reel systems, similar to center pivot and lateral-move platforms, can in principle be achieved through speed modulation, sectional control, or individual sprinkler control. In practice, however, commercial hose reel systems currently rely exclusively on speed-based VRI, where application rates are adjusted by modulating the retraction speed of the boom cart. This approach is simple and typically implemented using mechanical or programmable speed tachometers (see Figure 2.2). However, its spatial resolution is inherently limited to the width of the boom. Fertigation is also routinely implemented in these systems by injecting nutrients into the feed line of the HIS.

Extending hose reel systems beyond speed-controlled VRI/VRFI introduces significant technical challenges, as all components required for adjusting water and nutrient rates – such as fertilizer tanks, pumps, valves, and dosing units – must be installed directly on the mobile cart. This adds complexity, weight, and potential maintenance issues, while the cart must remain transportable and mechanically robust under field conditions. As a result, current HIS are generally limited to speed control. Polat and Çolak (2024) developed a speed-controlled HIS for fertigation, but it lacked section control and did not allow for independent adjustment of water and fertilizer rates, as both components were mixed at the system inlet.

To the best knowledge of the author, no implementation of section-controlled VRFI in hose reel systems exists beyond the experimental prototype developed within the ADDFerti project.

2.2 Theoretical Foundations of Site-Specific Application Map Creation

The creation of site-specific application maps is a core aspect of VRFI. These maps translate spatial information about soil, crop, and environmental variability into actionable input recommendations for water and fertilizer. This section outlines the conceptual and methodological foundations of site-specific prescription generation.

Crop growth is limited by the scarcest essential factor, as described by Liebig's *Law of the Minimum*. His later *Law of the Optimum* refines this concept, stating

that each growth factor (e.g., nutrients, water, light) has an ideal range – outside of which plant performance declines. Figure 2.3 illustrates this relationship: yield increases with nutrient availability up to a minimum optimal threshold, plateaus across a certain range, and may decline if concentrations exceed the optimal maximum (Incrocci et al., 2017).

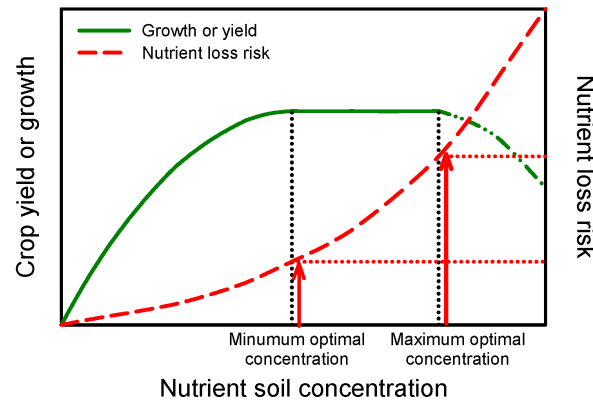


FIGURE 2.3: Relationship between crop growth (or yield) and nutrient soil concentration in the root zone. Source: Incrocci et al. (2017).

The goal of VRFI is to deliver water and nutrients in the right amount, at the right place, and at the right time. This requires a theoretical understanding of field heterogeneity. Six categories of spatial and temporal variability commonly affect agricultural production (Zhang et al., 2002):

- **Yield variability:** Past and present yield patterns offer insights into underlying productivity differences.
- **Field variability:** Topographic factors such as elevation, slope, and proximity to water bodies, that influence runoff, erosion, and microclimate.
- **Soil variability:** Chemical properties: nutrient concentrations (N, P, K, Ca, Mg, C, Fe, Mn, Zn, Cu), pH and cation exchange capacity (CEC); physical properties: soil type, bulk density, soil depth, field capacity (FC), permanent wilting point (PWP).
- **Crop variability:** Crop density, crop height, biomass, crop nutrient and water stress, crop grain quality.
- **Anomalous factors:** Biotic and abiotic stresses such as weeds, pests, diseases, or weather damage, which can alter local resource demands.
- **Management variability:** Differences in seeding rates, tillage practice, historic crop rotations and previous input applications that entail legacy effects in the field.

Some types of variability, such as field topography and management practices, are typically well known to farmers. Yield data is also commonly collected by modern combine harvesters. Other forms of variability, however, require targeted monitoring and sampling using dedicated methods and sensors, as described in Section 2.3.

While many of these variability types are interrelated, yield variability is typically treated as the integrative outcome, reflecting the cumulative effects of other factors. Importantly, variability is not only spatial but often temporal as well. For example, weed patches may shift within a season, and rainfall patterns can vary both in time and across small spatial scales. This highlights the importance of constant monitoring of field conditions, to keep prescriptions up to date (Zhang et al., 2002).

To manage spatial variability, fields are commonly divided into management zones (MZs). MZs are defined as sub-regions with similar characteristics and are typically delineated using a combination of spatial variables (Nawar et al., 2017). When based on stable attributes—such as topography, soil type, or water-holding capacity—the configuration of MZs can remain valid over multiple years. In contrast, MZs based on dynamic factors, such as crop stress, may even require in-season updates.

MZs are application-specific: separate MZ layers are created for different purposes such as fertilization, irrigation, or liming, using only the variables relevant to each input. Proxy variables are often employed when direct measurements are unavailable or too expensive. Even when direct measurements exist, including proxy variables can enhance spatial resolution or robustness.

Nawar et al. (2017) suggests five steps to delineate and verify MZs: (1) mapping variables, (2) clustering, (3) finding the optimal number of classes, (4) delineating final MZs, and (5) evaluating the effectiveness of the MZs. Once delineated, MZs can be used to generate application maps (often also referred to as "prescription maps" in agronomic literature) which specify the water and fertilizer rates to be applied in each zone. Figure 2.4 illustrates this general workflow. The following sections describe each step in more detail.

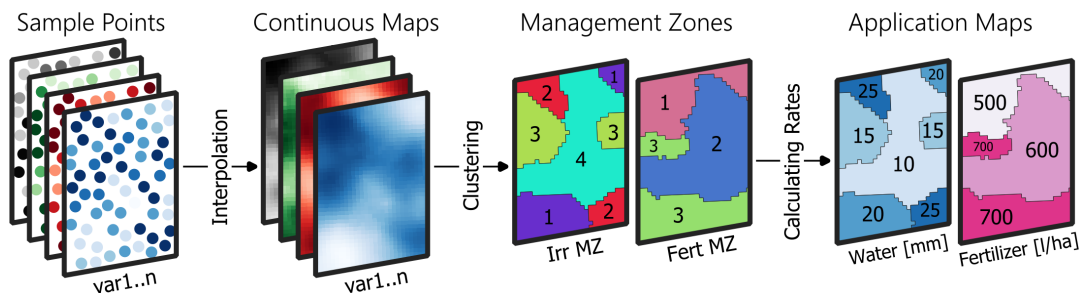


FIGURE 2.4: General workflow for creating site specific application maps.

2.2.1 Mapping Variables

Many variables used for MZ delineation are derived from point-based soil sampling and must be interpolated into continuous surfaces. This is achieved through spatial interpolation methods, which estimate values at unsampled locations based on nearby observations, considering the data's spatial structure. Common techniques include inverse distance weighting (IDW), kriging, and splines (Kumar and Sinha, 2018).

For remote sensing and UAV (unmanned aerial vehicle) imagery, interpolation is generally unnecessary, as these data sources already provide continuous spatial coverage. However, standard preprocessing steps (e.g., resampling, masking) and the calculation of vegetation indices and other derived parameters (e.g., NDVI, crop height) are typically applied to harmonize datasets and extract relevant information.

The accuracy of these maps—whether interpolated or remotely sensed—has a major impact on MZ delineation. Preprocessing, outlier removal, and validation against ground truth data are therefore essential to ensure spatial reliability.

2.2.2 Delineating MZs

Once spatial variables have been mapped, the next step in the creation of MZs is the delineation of sub-regions with similar characteristics. This is typically done using unsupervised classification methods, where clustering algorithms group spatial units based on similarities in soil, crop, or topographic attributes without prior labeling. The goal is to minimize variability within zones while maximizing contrast between them. Nawar et al. (2017) describes four different techniques frequently used for clustering:

- **Principal Component Analysis (PCA):** Not a clustering method itself, but often used as a preprocessing step to reduce dimensionality and highlight correlated attributes in multivariate datasets.
- **k-means clustering:** A partitioning algorithm that assigns data points to κ clusters by minimizing the within-cluster sum of squares. It is widely used for its simplicity and efficiency, though it assumes spherical clusters and equal variance.
- **Hierarchical clustering:** Constructs a nested tree-like structure (dendrogram) based on pairwise similarity. It does not require a predefined number of clusters but can be computationally demanding for large datasets.
- **Self-Organizing Maps (SOMs):** An artificial neural network that projects high-dimensional data onto a lower-dimensional grid while preserving topological relationships, making it well-suited for visualizing complex spatial patterns.

These methods can be applied to either individual or composite input layers – for example, to principal components derived from soil and crop data. The choice of clustering algorithm depends on the characteristics of the input data and the desired balance between interpretability and spatial cohesion. As there is no universally accepted standard for clustering in MZ delineation (Guastaferro et al., 2010), this remains an active area of research. For instance, Córdoba et al. (2013) propose a combined approach using spatial principal component analysis (sPCA) followed by fuzzy k-means clustering.

The optimal number of MZ classes can be quantified using specific indicators – depending on the clustering method used. In k-means clustering for example, the optimal number of classes is typically found by evaluating how much within-cluster variance (e.g., in yield or soil properties) is reduced as κ (the number of clusters) increases (Nawar et al., 2017). Furthermore the minimum size and shape of zones must be compatible with the capabilities of field machinery. Although modern GNSS-enabled application systems allow for fine spatial control, operational constraints such as the minimum controllable resolution of the fertigation system, field access, and field geometry may require smoothing or simplification of cluster boundaries (Zhang et al., 2002).

2.2.3 Validation of Management Zones

There are a few methods and indices to quantify the theoretical correctness of the delineated MZs, before they are used for VR applications.

A common approach is to perform a one-way analysis of variance (ANOVA) to test whether key variables – such as yield, soil properties, or NDVI – differ significantly between zones. A statistically significant result indicates that the zones effectively separate the field into distinct sub-regions with different characteristics.

Another useful metric is the ratio of between-zone to total variance, often referred to as the explained variance (R^2_{R2}). A high R^2_{R2} value suggests that a substantial portion of spatial variability is captured by the zone configuration, supporting its use for differential management.

For clustering-based delineation methods, internal validation indices such as the Davies-Bouldin Index (DBI), Silhouette Index (SI), or Calinski-Harabasz Index (CHI) can provide additional insights into the quality of the clustering. These indices evaluate aspects such as cluster compactness and separation, helping to assess how well the clustering reflects distinct spatial patterns.

In addition to statistical validation, visual validation is an often used method. By overlaying MZ boundaries on raw or interpolated input maps – such as yield or soil property layers – experts can judge whether the spatial configuration of the zones aligns with known field heterogeneity or management history.

Finally, ground truthing offers a direct means of validation. Additional soil or crop measurements can be collected from within each zone and compared to the data used for delineation. If large discrepancies are observed, this may

indicate that the zone definitions are unstable, overfitted, or not generalizable to actual field conditions.

2.2.4 Setting Fertigation rates

Once MZs have been delineated, the next step is to assign the specific fertigation rates to each zone. The goal is to match site-specific crop demand with fertilizer and water supply, accounting for variability in soil properties, crop growth, and environmental conditions. Rate determination can follow (1) empirical, (2) model-based, or (3) sensor-driven approaches, depending on the available data and system complexity.

In practice, combinations of these methods are often employed. For example, empirical rules may be changed based on observed crop growth variations, or model-based recommendations may be dynamically adjusted using real-time soil moisture sensor data. Regardless of the underlying method, practical constraints must be considered – including nitrate regulations, the practical upper and lower bounds of application rates for the irrigation system, and often simply the personal preferences of farmers.

Empirical Approaches

A common method for setting fertilizer rates is to apply relative to the UR. For example, MZ1 (low fertility) might receive UR + 20 %, MZ2 (medium fertility) the baseline rate (UR), and MZ3 (high fertility) a reduced rate of UR - 20 %. These empirical strategies often rely on expert knowledge, historic yield, or legacy soil maps. While straightforward and easy to implement, their accuracy may be limited, particularly under changing field conditions.

Model-Based Approaches

Model-based approaches aim to quantify fertigation needs more rigorously. For nutrient applications, zone-specific uptake targets can be estimated from target yields and matched against available nutrient supply, based on either laboratory soil analyses or soil sensing data. This results in a nutrient balance approach:

$$\text{Fertilizer dose} = \text{Crop demand} - \text{Soil supply} - \text{Residual contribution}$$

Dynamic models may additionally account for nutrient mineralization from organic matter, immobilization, fixation, volatilization, and leaching losses (Incrocci et al., 2017). An example is the SALUS model (Basso and Ritchie, 2015), which simulates crop response to management practices using input data such as weather conditions, silt and clay content, bulk density, organic carbon, soil hydraulic properties, and the initial soil water and nitrogen status.

For water applications, irrigation rates can be estimated through evapotranspiration (ET) models, soil water balances, or mechanistic simulation tools. The FAO Penman-Monteith equation remains a widely used standard for calculating reference evapotranspiration (ET_0) (Allen et al., 1998), with crop-specific coefficients (K_c) used to derive actual crop evapotranspiration (ET_c). Under non-standard conditions, ET_c can be adjusted using stress coefficients (K_s) to reflect salinity, pest pressure, or suboptimal management.

Sensor-Driven Approaches

Sensor-driven approaches are predominantly used in irrigation management. Data from soil moisture probes (e.g., TDR, FDR), in-situ nutrient sensors, or plant-based indicators (e.g., leaf water potential, canopy temperature, chlorophyll content) are integrated into a DSS. These systems may use rule-based logic, process-based models, or machine learning algorithms to translate sensed data into irrigation and fertilization prescriptions. Typically, sensors and DSS work in conjunction with automated irrigation hardware, enabling automatic VRFI without manual intervention. Sensor-driven methods allow for dynamic in-season adjustments based on actual field conditions and support both scheduled and demand-based fertigation.

2.2.5 Evaluating VRFI Effectiveness

After implementation, the effectiveness of VRFI strategies can be assessed by evaluating whether it led to measurable agronomic or economic improvements compared to uniform management. Key indicators include yield performance, fertilizer use efficiency, and net economic return. Spatial correlation between yield maps and MZ boundaries provides insight into whether applied rates matched underlying productivity potential. Quantitative indices, such as the Nitrogen Use Efficiency (NUE) (Dobermann, 2005), or more general input efficiency metrics, are often employed for this purpose.

In addition to these agronomic metrics, broader economic and environmental assessments may be applied. Cost-Benefit Analysis (CBA) can help determine whether the increased complexity and potential equipment costs of VRFI are offset by gains in productivity or input savings. Furthermore, Life Cycle Analysis (LCA) offers a approach to evaluate the environmental footprint of the VRFI strategy, including impacts related to energy use, greenhouse gas emissions, and nutrient leaching.

Ideally, the VR strategy should demonstrate both agronomic validity and practical benefit under real-world field conditions, while also contributing to improved economic viability and environmental sustainability.

2.3 Sensor Technology for soil and crops

Accurate soil and crop sensing is fundamental for PA by providing data to understand spatial and temporal field variability. This section discusses the

role of sensing technologies, key methods available, and their applications in soil and crop assessment, yield mapping, and remote sensing.

Sensing technologies play a critical role in modern PA in general as well as for VR irrigation and fertilization in particular by providing data to understand spatial and temporal field variability. To have access to precise and timely sensor data is important, because it enables data-driven decision-making in agriculture, allowing for optimized resource allocation, improved crop health monitoring, and increased operational efficiency. Besides the creation and adjustment of fertigation application maps, other applications enabled by sensor data include pest and disease detection, real-time monitoring of crop health, VR seeding, and automated weed management.

For VRFI, several key parameters can be monitored to ensure precise and efficient input management. These include soil properties and nutrients, soil moisture, crop status, yield, and climatic conditions:

Soil Properties and Nutrients Accurate sensing of soil properties and nutrient levels is fundamental for data-driven irrigation and fertilization strategies. Commonly measured parameters include macronutrients (N, P, K), micronutrients (Mg, Ca, Fe, Mn, Zn, Cu), pH, organic matter content, soil moisture, and texture.

Soil Moisture Monitoring soil moisture is critical for directly calculating irrigation needs and for the adjustment of irrigation models.

Crops Monitoring crop growth and health reveals the spatial and temporal variability in plant development. Crop sensing provides key indicators such as biomass accumulation, chlorophyll content, canopy temperature, and stress signals related to water or nutrient deficiencies. Crop monitoring can support the dynamic adjustment of application rates in response to current crop demand.

Yield Specialized machinery can monitor grain mass, volume, and quality indicators during harvest, to evaluate crop performance and refine zone-specific management for subsequent growing seasons.

Climate and Weather Environmental conditions, such as temperature, humidity, precipitation, wind speed, and solar radiation, have a direct impact on crop growth, evapotranspiration, and soil water dynamics. Continuous monitoring of local weather is crucial for irrigation scheduling and supports predictive decision-making models.

When planning data collection campaigns in the field, it is essential to align measurement frequency and spatial resolution with the specific requirements of each application. From a temporal perspective, parameters, such as soil moisture or the crop health, require continuous or frequent monitoring due to their dynamic nature and immediate impact on irrigation decisions. In contrast variables such as soil fertility may only need seasonal assessments.

Furthermore, the required spatial resolution largely depends on the heterogeneity of soil conditions within an individual field and the desired precision

of the application. This influences factors such as the number of soil samples required per hectare or the choice of the sensor system, for instance, satellite remote sensing versus UAV-based sensing. Balancing spatial resolution with operational feasibility enables efficient data collection while maintaining accuracy in precision farming applications.

In general, the necessity of soil sensing always needs to be looked at from an economical standpoint, often times the use of proxy variables can substitute expensive soil sampling campaigns (Nawar et al., 2017).

The Internet of Things (IoT), which has seen significant advancements across various fields in recent years, has also found its way into precision farming (Xu et al., 2022). IoT integrates smart sensors with networked communication, enabling real-time data collection and analysis in PA. This technology relies on interconnected devices equipped with sensors that communicate wirelessly through protocols such as LoRaWAN, NB-IoT, and Zigbee. The collected data is transmitted to cloud-based platforms or edge computing systems, where it is processed, analyzed and presented in the form of dashboards, maps, tables and charts.

In arable precision farming, a variety of in situ sensor types are utilized to enhance PA practices. The most commonly used sensors include positioning sensors, which are crucial for accurate field operations; optical sensors, capturing reflected electromagnetic spectra at various wavelengths for crop and soil analysis; electrical and electrochemical sensors, measuring electrical conductivity, resistance, or chemical composition to assess soil moisture, pH, and nutrient levels; mechanical and pressure sensors, providing data on soil compaction; and environmental and meteorological sensors, which monitor climatic conditions.

These sensors can be deployed on various platforms depending on their characteristics, including handheld devices, vehicle-mounted systems, stationary sensors, UAVs, planes, or satellites.

2.3.1 Soil Property and Nutrient Sensing

Depending on the application scale and required accuracy, various soil sensing techniques may be employed, this includes methods such as visible and near-infrared (vis-NIR) spectroscopy, electromagnetic induction (EMI), Gamma-ray spectrometry, or soil sampling with laboratory analysis. An overview of these techniques is provided by Gebbers (2018).

Traditional soil analysis is conducted through manual or automated soil core sampling, involving three main steps: sample collection, transportation to a laboratory, and subsequent analysis. While this method remains the most precise at point-scale, it is inherently time-consuming, labor-intensive, and costly at each stage. Consequently, it is less suitable for field-scale or high-frequency monitoring. However, laboratory-based soil sampling is particularly valuable for calibration and validation of sensor-based measurements, for establishing baseline nutrition levels at the beginning of a growing season

using mixed samples, and for research applications that require high analytical accuracy across multiple parameters.

The required spatially dense soil sampling can be achieved using sensor-based methods mounted on vehicles, robotic platforms, or as handheld devices. These sensors detect physical signals, such as light, heat, or electromagnetic radiation, and convert them into digital outputs, for example voltage. Common modalities include optical, thermal, electromagnetic, and electrochemical sensing. Accurate soil property estimation depends on well-calibrated relationships between the sensor signals and soil attributes. To improve reliability and to capture a broader range of characteristics, multi-sensor platforms employing sensor fusion are often used (Najdenko et al., 2024).

Recently, handheld soil sensors have been introduced, capable of delivering real-time results with minimal effort (Pal et al., 2024). These devices often integrate multiple sensor technologies – such as optical, electrochemical, and electromagnetic sensors – alongside advanced algorithms to assess soil properties and nutrient levels with high efficiency. One of the handheld soil sensors recently introduced to the market is the FarmLab, developed by the German company Stenon. This sensor was also utilized in field experiments conducted for this study and will be discussed in further detail in Section 4.4.

Electromagnetic Induction (EMI)

EMI is a popular non-invasive technique used to map the apparent soil electrical conductivity (EC_a), which correlates with key soil properties such as moisture content, texture, salinity, pH, organic matter, and cation exchange capacity. EMI instruments generate a primary magnetic field that induces eddy currents in the soil; the resulting secondary magnetic field is then measured to derive EC_a values.

EMI sensors are typically mounted on a sledge or platform towed behind a vehicle and can be operated in different coil configurations to target varying soil depths. They enable rapid, continuous mapping of soil properties at field scale. Doolittle and Brevik (2014) provide an overview of previous studies and agricultural applications of EMI. Although EMI does not measure specific nutrients, it is often combined with complementary sensing techniques, such as vis-NIR spectroscopy, to enhance soil characterization.

Soil spectroscopy

In the last two decades, soil reflectance spectroscopy has emerged as a viable alternative to traditional methods, offering a rapid and cost-effective approach to soil analysis (Stenberg et al., 2010). In-field soil spectroscopy is commonly used to measure a range of soil properties with accuracies comparable to laboratory analysis (Soriano-Disla et al., 2017; Ahmadi et al., 2021). These include soil nutrients such as N, P, K, Ca, Mg, Fe, and Mn, as well as pH, CEC, texture, soil moisture and SOC (Mouazen et al., 2006; Vohland et al., 2014).

TABLE 2.1: Overview of common spectral regions used in soil spectroscopy. Source: Gebbers (2018), modified.

Spectral Region	Abbr.	Wavelength Range	Typical Applications in Soil Science
Ultraviolet	UV	200–400 nm	Detection of organic compounds
Visible	Vis	400–780 nm	Soil color, iron oxides
Near-Infrared	NIR	0.75–1.1 μm	Texture, moisture, organic carbon, general compositional assessment
SWIR	SWIR	1.1–2.5 μm	Clay minerals, CEC, nutrients
MIR	MIR	2.5–25 μm	Mineral identification, organic groups

Soil spectroscopy is a non-destructive analytical technique that analyzes the interaction of electromagnetic radiation within specific wavelength ranges (see Tab. 2.1) with soil constituents to deduce their chemical and physical properties. When photons from a light source strike the soil, specific wavelengths are absorbed or reflected based on the molecular bonds and mineral structures present. These spectral responses, captured by spectrometers, generate a unique reflectance spectrum that serves as a fingerprint of the soil's composition. Visible (Vis) and UV spectrophotometers work on the principle of the interaction of visible or UV light with the electrons in the atoms. Photons of specific energies or wavelengths are absorbed due to the excitation of electrons. For longer wavelengths, such as IR spectroscopy, infrared radiation causes molecular bonds in soil constituents to vibrate, absorbing specific energy quanta based on their chemical context (Miller, 2001; Stenberg et al., 2010).

A wide range of spectrometers is available for soil sensing, varying in spectral range, resolution, and channel density. For proximal soil spectroscopy, the most relevant is the visible-near-infrared (vis-NIR) range, which enables the estimation of key properties such as SOC, nutrients, soil moisture, texture, pH, CEC, and heavy metals – either directly or via correlated signals (Stenberg et al., 2010). Vis-NIR sensors are fast, robust, and cost-effective, but their spectra are often relatively unspecific, requiring extensive data preprocessing and calibration. Consequently, research has focused on building spectral libraries (Safanelli et al., 2023), spectral preprocessing methods (e.g., baseline correction, normalization, filtering, and derivatives), and developing calibration models using methods such as partial least squares regression (PLSR), support vector machines (SVM), artificial neural networks (ANN), and random forests.

For field sampling, spectrometers can be mounted on mobile sensor platforms, handheld devices, or soil probes that are placed in direct contact with the soil. Paired with a mobile platform, soil spectroscopy enables more frequent and spatially dense soil sampling at a lower cost, allowing farmers to generate accurate soil maps. From a research perspective, such data also enhance the understanding of soil heterogeneity and spatiotemporal dynamics, particularly

in relation to key topics such as the soil nitrate cycle (Giles et al., 2012; Elrys et al., 2021) and long-term soil carbon stock changes (Ellili et al., 2019).

Gamma-ray spectrometry

Gamma-ray spectrometry (GRS) is a passive sensing technique that detects and quantifies gamma radiation emitted by the natural decay of radionuclides such as ^{40}K , ^{238}U , and ^{232}Th (Reinhardt and Herrmann, 2019). It was originally applied for uranium exploration in the late 1940s (Mero, 1960) and has since gained relevance in soil science. The concentration of naturally occurring radionuclides varies with soil type and mineral composition, allowing GRS to characterize the spatial distribution of soil properties. It can be deployed in either ground-based or airborne configurations.

In agriculture and soil science, GRS is primarily used to assess soil texture, mineralogy, and contamination; it has also shown potential for mapping pH and SOC (Dierke and Werban, 2013; Reinhardt and Herrmann, 2019). Ongoing research is evaluating its suitability for estimating soil nutrient content, although results remain inconclusive and are often site-specific (Wong and Harper, 1999; Reinhardt and Herrmann, 2019; Poncet et al., 2021).

2.3.2 Soil Moisture Sensing

There are multiple methods to measure soil moisture (SM), Shamshiri et al. (2022) gives a general overview. In the context of site-specific irrigation in arable farming, stationary in-field sensors and remote sensing represent the most relevant and widely adopted approaches for continuous and scalable SM monitoring. Other techniques—such as handheld sensors and gravimetric (laboratory) analysis—are primarily used for calibration, validation, and research purposes, where high accuracy is required at specific locations.

Stationary soil moisture sensors

For stationary SM monitoring in the field, electrical sensors are the most practical and widely used, offering advantages over techniques such as tensiometers and neutron probes. Electrical sensors are categorized as resistive or capacitive, with resistive sensors being inexpensive (1 to 15 €) but often lacking accuracy (Saleh et al., 2016). The most commonly employed methods are frequency-domain (FDR) and time-domain reflectometry (TDR). TDR measures SM by determining the dielectric constant, whereas FDR uses an oscillating circuit to assess the apparent dielectric permittivity (ϵ). FDR sensors are widely adopted due to their simplicity, cost-effectiveness, and rapid response times, although their accuracy can be influenced by variations in soil salinity, temperature, and texture. In contrast, TDR sensors offer higher accuracy and are less affected by salinity, temperature, and texture, but tend to be more expensive than FDR sensors (Mittelbach et al., 2012). Stationary SM sensors are typically equipped with a data logger or an IoT-based data connection.

Remote soil moisture sensing

Remote sensing (RS) provides a non-invasive means of assessing soil moisture over large areas. The most commonly used remote sensing techniques include optical, thermal infrared, and microwave sensing. RS data can be acquired via UAVs, aircraft, or satellites, depending on the availability and the spatial and temporal resolution required.

Optical remote sensing (4-7 μm) estimates SM by analyzing surface reflectance changes. Moist soil appears darker due to increased absorption of visible and near-infrared (NIR) light, whereas dry soil reflects more light, appearing brighter. However, optical remote sensing of soil moisture is highly sensitive to surface conditions, particularly vegetation cover and atmospheric interference such as cloud cover, haze, or aerosols.

Thermal infrared remote sensing (8-12 μm) measures surface temperature variations. Since moist soil has a higher heat capacity than dry soil, it heats and cools more slowly (morning warming & evening cooling). This temperature contrast allows for indirect SM estimation. Though accuracy can be affected by surface roughness, vegetation cover, and diurnal temperature fluctuations. Both optical and thermal methods are restricted to the uppermost millimeters of the soil and are best suited for assessing short-term moisture changes at the surface of bare soils.

Microwave remote sensing (5mm-40cm) has emerged as the most promising approach for large scale SM retrieval due to its ability to penetrate cloud cover, vegetation, and, depending on the frequency, the upper few centimeters of the soil profile (Karthikeyan et al., 2017). The measurement principle is based on the strong relationship of the soil's dielectric properties to changes in moisture content, given the pronounced contrast between the dielectric constants of water and dry soil. These variations in dielectric properties are detected either through the observation of naturally emitted microwave radiation using passive systems (radiometers), or by measuring the backscatter of transmitted signals with active systems (synthetic aperture radar, SAR).

Reliable SM estimates from microwave remote sensing require ground truth data for calibration and validation. This typically includes in-situ measurements from stationary sensors and gravimetric samples. Additionally, the International Soil Moisture Network (ISMN⁶) provides global access to in-situ SM data from various long-term monitoring networks, serving as a key reference for validating remote sensing products.

However active microwave signals are susceptible to surface roughness, and vegetation cover, requiring advanced correction models for accurate interpretation. (Akash et al., 2024) gives an introduction on how to estimate SM using microwave remote sensing, while (Xu et al., 2025) provides a review about the accuracies for different frequencies, models and sensor types in microwave remote sensing.

⁶International Soil Moisture Network: <https://ismn.earth>

Current microwave satellite missions are limited to measuring SM in the top 2-10 cm of the soil profile. These missions typically employ C-band (~5 cm wavelength), S-band (10 cm) and L-band (~20 cm) systems (see Table 2.2). To overcome this limitation, several studies have applied machine learning to estimate root-zone SM by enriching L-band microwave data with additional inputs such as climate variables, elevation, soil texture, and vegetation patterns (Zeng et al., 2019; Karthikeyan and Mishra, 2021; Brakhasi et al., 2023). Brakhasi et al. (2023) also proposed the use of longer wavelengths such as P-band (~40 cm), as this frequency may enable the direct retrieval of SM from within the root zone.

TABLE 2.2: Overview of current microwave remote sensing missions¹.

Mission	Sensor Type	Resolution	Depth	Revisit	Launch	Agency
SMOS	L-band (passive)	35–50 km	~5 cm	2–3 days	2009	ESA
Sentinel-1	C-band SAR	10–20 m	~2–5 cm	12 days ²	2014	ESA
SMAP	L-band (passive)	9–36 km	~5 cm	2–3 days	2015	NASA
SAOCOM	L-band SAR	10–100 m	~5–10 cm	8 days	2018	CONAE (Arg)
RADARSAT	C-band SAR	5–100 m	~2–5 cm	4 days	2019	CSA (Can)
RISAT-1A	C-band SAR	1–50 m	~2–5 cm	12 days	2022	ISRO (Ind)
NISAR	L-/S-band SAR	3–10 m	~5–10 cm	12 days	2025 ³	NASA/ISRO

¹ The eoPortal, operated by ESA, provides a complete list of all launched and planned Earth observation satellite missions (<https://www.eoportal.org/about-eoportal>).

² Due to the equipment failure of S-1B, the revisit interval for Sentinel-1 SAR data increased from 6 to 12 days, as only S-1A remained operational. To restore coverage, S-1C was launched in December 2024 and is currently undergoing commissioning.

³ Planned to be operational in early 2026.

From a spatial resolution perspective, passive microwave sensors are limited to regional scales of several tens of kilometers, rendering them unsuitable for site-specific water management. In contrast, active systems such as Sentinel-1 (S-1) provide resolutions suitable for plot-scale SM mapping. Especially the newer systems RISAT-1A and the planned NISAR with 1–50 m and 3–10 m resolution respectively are promising. However, SAR is sensitive to surface roughness and vegetation cover, complicating the retrieval process. While vegetation effects can be mitigated using indices like NDVI derived from Sentinel-2, accurate surface roughness correction requires knowledge of current field conditions (El Hajj et al., 2017).

Xu et al. (2025) reported that in previous studies SM retrieval from Sentinel-1 (n=31) and RADARSAT (n=12) achieved a coefficient of determination $R^2 = 0.7$ and a RMSE of $0.04 \text{ m}^3/\text{m}^3$ in median. However, studies by Bazzi et al. (2024) demonstrated that S-1 SM retrievals are reliable only under low to moderate vegetation conditions, specifically when the NDVI is below 0.7. Attarzadeh et al. (2018) combined S-1 with optical S-2 data and achieved through support vector regression an estimation accuracy for surface SM (0–5 cm) of 4.94% RMSE and $0.89 R^2$.

Microwave remote sensing remains a highly active research field, particularly in efforts to enhance retrieval accuracy under diverse surface conditions. In recent years, several new L and C-band SAR satellite constellations have been

launched (or are planned) that offer improved spatial resolution and a broader range of frequencies. Although the SM retrieval capabilities of these missions are not yet fully characterized, they show strong potential for supporting VRI applications through more accurate and scalable monitoring of SM.

2.3.3 Crop Sensing

Crop sensing can be performed using ground-based platforms (e.g., handheld or tractor-mounted sensors), UAVs, or satellite imagery. Key parameters typically assessed include biomass, chlorophyll content, leaf area index (LAI), and indicators of plant water status.

Remote and proximal crop sensing methods rely primary on optical and thermal measurements, particularly in the visible (vis), near-infrared (NIR), and shortwave-infrared (SWIR) spectral ranges. Multispectral imaging involves capturing data at specific wavelengths across the electromagnetic spectrum, often utilizing vegetation indices (VIs) to assess plant health. Table 2.3 shows a selection of the most used VIs in crop remote sensing. Studies have demonstrated strong correlations between these indices and crop characteristics such as LAI and biomass (Hatfield and Prueger, 2010). However, factors like soil background, atmospheric conditions, and sensor calibration can influence the accuracy of these indices.

TABLE 2.3: Selection of commonly used vegetation indices in crop monitoring.
Source: Vidican et al. (2023), modified.

Index ¹	Bands	Main Use	Key Strength
NDVI	NIR, Red	Early to mid growth stages	Simple, robust, and widely supported
EVI	NIR, Red, Blue	Dense crops, advanced growth	Corrects for atmospheric and soil background effects
NDRE	NIR, Red Edge	Later growth stages	Sensitive to chlorophyll and nitrogen content
VARI	Red, Green, Blue	When NIR data is unavailable	Optimized for RGB imagery from UAVs

¹ NDVI: Normalized Difference Vegetation Index, EVI: Enhanced Vegetation Index, NDRE: Normalized Difference Red Edge, VARI: Visible Atmospherically Resistant Index.

Thermal imaging captures canopy temperature, which reflects plant water status via its relationship with transpiration. Under water stress, stomatal closure reduces transpiration, raising leaf temperatures. The Crop Water Stress Index (CWSI) quantifies this by comparing canopy and air temperatures. The Water Deficit Index (WDI) builds on this concept by integrating a vegetation index (VI) with the composite land surface temperature (LST) to account for both greenness and thermal conditions (Hoffmann et al., 2016).

Regarding satellite-based crop sensing platforms, Sentinel-2 provides free imagery with 10 m resolution for visible and NIR bands. While sufficient

in many cases, this resolution may be inadequate for fields with complex, small-scale geometries or high crop heterogeneity in general. Commercial constellations such as PlanetScope offer daily imagery at 3-5 m resolution, albeit on a subscription basis. A major limitation of optical satellite sensing remains its susceptibility to cloud cover, which can severely restrict data availability in many regions worldwide during key growth stages.

UAVs are increasingly used for high-resolution crop monitoring. Equipped with multispectral, thermal, or RGB cameras, UAVs can capture spatially detailed crop data at flexible time intervals (Grenzdörffer et al., 2008). Advances in UAV autonomy and onboard computing have enabled fully automated workflows, including mission planning, navigation, data acquisition, and cooperative operation in the form of "drone swarms" (Ming et al., 2023). One of the latest developments is the fully automated deployment of UAVs via "drone-in-a-box" systems, which enable continuous, unattended operation for routine crop monitoring (DJI, 2024).

Among handheld sensors, chlorophyll meters are the most widely used. They typically rely on narrowband light-emitting diodes (LEDs) and photodiodes to measure light transmittance through the leaf at multiple wavelengths, allowing the calculation of chlorophyll indices. These devices are now well established on the market, and even relatively low-cost instruments (ca. €300) have demonstrated good accuracy (Brown et al., 2022).

2.3.4 Yield Sensing

Yield sensors are routinely integrated in combine harvesters and record parameters such as grain mass flow, moisture content, and spatial position (via GNSS) in real time. Various sensing principles are applied, including optical, impact plate, and load cell-based measurements. These systems are calibrated to convert sensor signals into accurate yield estimates, which are georeferenced to produce high-resolution yield maps. Fulton et al. (2018) provides a guide on how to process and interpret yield monitor data.

While yield sensing is most commonly applied to cereal crops such as wheat, maize, and barley, its adoption for other crops (e.g., potatoes, sugar beets) remains limited due to technical challenges in sensor design and the variability of harvesting machinery.

Yield maps should be interpreted in the context of current-season variability, as spatial yield patterns often shift between years due to the dynamic interaction of soil properties, crop types, and weather conditions during the growing cycle (Blackmore et al., 2003). Consequently, historical yield maps should be used cautiously for decision-making (Bill et al., 2022).

2.4 ICT Components and Spatial Data Management

Farmers and agricultural service providers increasingly rely on software tools to support the planning, execution, and monitoring of field operations. This

section outlines the essential ICT components for implementing an automated VRFI system, namely GIS, SDI, FMIS, and DSS.

2.4.1 GIS - Geographic Information Systems

GIS is an essential tool in PA, as it enables the integration, analysis, and visualization of spatial datasets. Even when an automated DSS is used, the setup of a VRFI operation typically involves several preparatory steps conducted within a desktop GIS environment. One of the most fundamental tasks is the precise delineation of field or crop stand boundaries, ideally including tramlines, which serve as the basis for all subsequent planning. These boundaries can be digitized from high-resolution orthophotos or derived from high-accuracy differential GNSS (DGNSS) surveys (Bill et al., 2022).

GIS plays a key role in harmonizing heterogeneous spatial datasets. Typical preprocessing operations include trimming, reprojection, and resampling of input layers to ensure spatial alignment. GIS can also be used for interpolating point-based measurements—such as soil samples or sensor readings—and for generating derived layers like MZs. Additionally, it supports the processing of raw yield data into spatially explicit yield maps, enabling further analyses and integration into decision support workflows (Bill et al., 2022).

2.4.2 Databases

Relational databases form the backbone of SDIs and FMIS in PA, particularly in VRFI applications where large volumes of heterogeneous data must be stored, queried, and managed efficiently. Spatial extensions such as PostGIS for PostgreSQL enable the storage and processing of geographic objects alongside tabular data, enabling operations like spatial joins, buffering, and coordinate transformations. These capabilities are essential for harmonizing soil sensor data, weather forecasts, MZs, and application maps. When linked to web services or GIS clients, these databases support dynamic data retrieval and visualization, enabling real-time interaction with spatial datasets across DSS, FMIS, and field equipment (Nowak, 2021).

2.4.3 Data transfer and Standards

While the already mentioned ISOBUS provides a standard for wired communication between tractors and implements, no universal standard exists for wireless data exchange in PA. In practice, data transfer—such as yield data, documentation logs, and application maps—is often still handled via USB drives on farms (Nowak, 2021). Jackenkroll (2021) remarked that while the adoption of agricultural software is on the rise among farmers, a significant number still rely on printed application maps during field operations.

However, automated VRFI systems require continuous and reliable data exchange between multiple components, including sensors, DSS, and application equipment. To enable this, robust and interoperable interfaces must be

implemented. Depending on the system architecture and specific use case, different standards and protocols may be employed. These include RESTful APIs for cloud-based data synchronization, the MQTT (Message Queuing Telemetry Transport) protocol for lightweight sensor communication, and standardized web services of the Open Geospatial Consortium (OGC) for spatial data exchange. For in-field long-range communication, protocols like LoRaWAN or Zigbee are commonly used to transmit data from distributed IoT sensors (Shafi et al., 2019).

In recent years, major agricultural machinery manufacturers have begun offering web-based platforms. While many of these platforms are still limited in terms of openness and interoperability, there has been a gradual shift toward open data sharing facilitated by the use of open APIs (Jackenkroll, 2021). Such APIs enable communication between heterogeneous systems and devices, e.g. between ISOBUS and non-ISOBUS components.

Standards of the Open Geospatial Consortium

The OGC is a leading international body that develops open standards to ensure interoperability of geospatial data, services, and sensor networks across systems and organizations. Its specifications are widely adopted in public, academic, and commercial domains (Kresse et al., 2022). OGC services are standardized web service interfaces that function as geospatial APIs. OGC standards such as the *Web Map Service* (WMS), *Web Feature Service* (WFS), and *Web Coverage Service* (WCS) enable the seamless dissemination and access of geospatial data over the internet. In particular:

- **WMS** allows for rendering and visualizing map layers, e.g., NDVI maps or yield results, in web-based interfaces.
- **WFS** facilitates querying and exchanging vector-based spatial features such as field boundaries, sampling points, or MZs.
- **WCS** supports access to raster data with its underlying numerical values, which is essential for analysis tasks like interpolating soil nutrient concentrations or processing sensor-derived indices.

These services are complemented by the *Sensor Observation Service* (SOS) and other components of the Sensor Web Enablement (SWE) framework, which were developed to facilitate the integration and real-time data streaming from in-situ field sensors, as demonstrated by Geipel et al. (2015).

OGC standards can enable modular and interoperable geospatial infrastructures in PA, facilitating data and service exchange across diverse stakeholders such as equipment vendors, farm management platforms, and researchers (Nash et al., 2007). For VRFI applications, if correctly implemented, they may ensure seamless integration between DSS, SDI, and field machinery by standardizing the generation and transfer of spatially explicit application maps (Nash et al., 2009).

LoRaWAN Technology

LoRaWAN (Long Range Wide Area Network) is an open wireless communication protocol designed for long-range, low-bandwidth, and energy-efficient data transmission. Initially developed for IoT applications such as home automation, smart cities, and industrial logistics, it has increasingly gained traction in PA due to its suitability for wireless sensor networks in remote or infrastructure-poor environments. Typical applications in agriculture include greenhouses, orchards, and vineyards (Križanović et al., 2023).

LoRaWAN builds on LoRa, the physical layer is based on Chirp Spread Spectrum (CSS) modulation, which ensures a robust transmission even under noisy conditions. The protocol layer is defined by the LoRa Alliance. Communication ranges vary from about 2 km in urban areas to more than 40 km in rural settings, depending on terrain and transmission power. Although data rates are modest (typically below 250 bit s^{-1}), they are sufficient for transmitting periodic environmental measurements such as soil moisture, weather data, or tank levels. Devices are optimized for energy efficiency, with lifetimes of up to ten years under low transmission frequencies (e.g., three messages per hour). For example, with a 950 mAh 3.3 V battery, a five-year lifetime has been reported at a 30-second measurement interval (Bouguera et al., 2018).

The protocol supports bidirectional communication and defines three operational classes⁷: Class A (downlink only after an uplink), Class B (periodic downlink windows), and Class C (continuous downlink availability). The network follows a star topology: end devices transmit via LoRa modulation to gateways, which bridge the network to the internet via TCP/IP. Gateways forward the data to a network server for authentication, packet deduplication, and routing, before delivery to application servers where it can be processed, visualized, or integrated into a FMIS (see Figure 2.5).

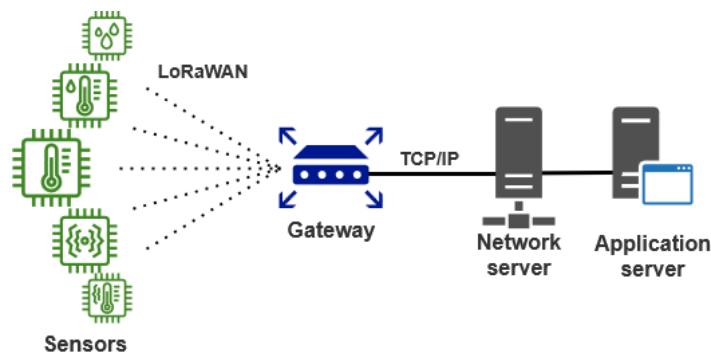


FIGURE 2.5: LoRaWAN network architecture.

Ongoing research focuses on improving coverage, throughput, scalability, robustness, and energy efficiency. Key parameters under investigation include the spreading factor (SF), which balances sensitivity and range against data rate and power consumption, and the coding rate (CR), which provides redundancy for error correction (Bouguera et al., 2018).

⁷<https://www.thethingsnetwork.org/docs/lorawan/classes>

Alternative LPWAN (Low Power Wide Area Network) technologies include NB-IoT and Sigfox. NB-IoT, standardized by 3GPP, operates in the licensed LTE spectrum and requires both SIM cards and subscriptions (e.g., about €1 per device for 1 years). While it offers reliable connectivity, its dependency on LTE coverage limits its suitability for some agricultural areas, and its battery life is generally somewhat shorter than that of LoRaWAN. Sigfox, in contrast, uses Binary Phase Shift Keying (BPSK) modulation within an ultra-narrow 100 Hz band. It achieves comparable range, data rates, and device lifetimes to LoRaWAN, but operates as a proprietary service relying on Sigfox's own base station network. Subscriptions typically cost around €5 per device per year, with good coverage across most of Europe, including Turkey (Mekki et al., 2018).

LoRaWAN has emerged as the most successful LPWAN technology in PA because it combines long-range communication and ultra-low power consumption with an open, license-free standard (Bouguera et al., 2018). Unlike Sigfox and NB-IoT, LoRaWAN allows users the flexibility to either set up their own local gateways or join subscription-based LoRaWAN networks (typically around €1 per sensor per year).

2.4.4 SDI - Spatial Data Infrastructures

SDIs provide the technical and organizational framework for publishing, sharing, and managing geospatial data across multiple actors. In PA, this includes farms, contractors, service providers, and public agencies. Beyond databases, SDIs encompass standardized interfaces, metadata, interoperability protocols, and user management.

SDIs can be implemented at various scales – from large national platforms hosting thousands of public datasets (Beyer et al., 2025) to ad-hoc deployments within research projects (Geipel et al., 2015) or as integrated components of a FMIS (Honda et al., 2014). By leveraging OGC standards, spatial datasets published through an SDI can be seamlessly integrated into third-party software such as dashboards, web applications, mobile tools, other SDIs, or even directly into the control terminals of PA machinery, as demonstrated by Kaivosoja et al. (2014).

Since PA is fundamentally reliant on geospatial data, the integration of SDI components is both logical and beneficial. In his PhD thesis, Jackenkroll (2021) developed SDI components tailored for PA and emphasized that structured data exchange is essential for operational workflows. He further notes that the use of standardized SDI frameworks not only facilitates internal data management but also enables interoperability with external domains, allowing the import of additional datasets as a benefit.

On the implementation level, open-source SDI platforms such as CKAN⁸ and GeoNode⁹ are currently the open source SDI projects with the most traction,

⁸<https://github.com/ckan>

⁹<https://github.com/GeoNode>

offering robust, extensible, and standards-compliant solutions for managing and publishing geospatial data.

Kaivosoja et al. (2014) presented a practical example of SDI integration in PA through the implementation of a data-driven precision spraying system combining a cloud-hosted SDI with a local DSS. The SDI was implemented using GeoServer¹⁰, GeoNetwork¹¹, and PostGIS, providing application maps and auxiliary geospatial layers – such as groundwater protection zones, flood risk areas, and background maps. An ISOBUS task controller on the tractor retrieved these datasets via WMS and WFS, while weather forecasts were downloaded from an FTP server. The on-board DSS applied a simple rule-based logic: the spray rate was calculated as the user-defined base rate multiplied by the site-specific application factor. Additionally, the system disabled spraying in case of imminent rainfall or when the machine entered a groundwater protection area.

Despite their potential benefits, SDI technologies have seen limited adoption in the agricultural sector, as noted by Bill et al. (2022). Most client software provided by public authorities and commercial FMIS vendors is either not SDI-compliant or only partially supports standardized interfaces. Instead, many of these systems rely on proprietary web services, which hinders interoperability and the seamless integration of geospatial data across platforms.

2.4.5 DSS - Decision Support Systems

DSS are digital tools designed to support complex decision-making processes by combining data, models, and user inputs to generate informed recommendations (Lindblom et al., 2017). In the specific context of fertigation, DSS integrate multiple data sources – including soil properties, crop development, weather conditions, and irrigation system characteristics – to provide site- and time-specific recommendations for nutrient and water application. DSS can apply rule-based logic, crop simulation models, or machine learning algorithms to optimize both the timing and dosing of inputs.

A key conceptual distinction in DSS design is between open-loop and closed-loop architectures (Navarro-Hellín et al., 2016). Open-loop systems generate static recommendations based on predefined models, historical data, or offline simulations. In the context of VRFI, this typically means that application maps are prepared in advance and implemented without further adjustments during operation. By contrast, closed-loop systems integrate real-time feedback – such as sensor data or updated weather forecasts, allowing them to adapt recommendations dynamically during the growing season.

DSS for irrigation and fertigation often focus on modeling crop water and nutrient demand. Rather than enforcing rigid prescriptions, many systems provide scenario-based suggestions or decision options, leaving the final decision in the hands of the farmer. Furthermore some systems assist in the

¹⁰<https://github.com/geoserver>

¹¹<https://github.com/geonetwork>

planning and operational phases, while others serve more general management functions (Bonfante et al., 2019).

Despite their potential, the widespread use of DSS in field-scale agriculture remains limited (Lindblom et al., 2017). As Lanucara et al. (2024) emphasize, many systems suffer from poor usability, lack of integration with existing farm workflows, and insufficient consideration of end-user requirements. Conventional graphical user interfaces (GUIs) may be unintuitive, and DSS outputs are often task-specific or narrowly focused, requiring farmers to rely on multiple systems for different aspects of management.

Examples of DSS in PA

A wide range of DSS have been developed to assist various aspects of PA. These systems vary in scope, technical architecture, and intended user groups – ranging from national-scale platforms to crop- and region-specific applications. While many DSS provide recommendations at the whole-field scale, some also support site-specific interventions. In general, irrigation-focused DSS are more mature and widely adopted in practice, whereas fertilization and fertigation DSS are less common

Irrigation-Focused DSS

IRRIFRAME (Italy) is a national UR irrigation DSS built on a water balance model. Users specify plot locations via a Google Maps interface and automatically receive environmental data including meteorology (ET, temperature, rainfall), soil texture, water table depth, and water availability. After entering crop and irrigation system details, the DSS generates a daily irrigation schedule by combining user input with site-specific data from public sources (Giannerini et al., 2015).

IrriSAT (Australia) is a VR remote sensing-driven irrigation DSS. It derives a specific crop coefficient (K_c) from NDVI using satellite imagery at 30 m resolution. Daily crop water use is calculated by multiplying K_c with reference evapotranspiration (ET_o) from nearby weather stations, to generate site-specific irrigation recommendations (Montgomery et al., 2015).

AquaCrop, developed by FAO, is a simulation-based DSS used internationally to assess crop water productivity under varying soil, climate, and management conditions (Steduto et al., 2009). Although it is not a web-based system, it is widely used in research and development projects. In practice, *AquaCrop* is primarily applied for UR irrigation, but in principle it can also be parameterized for specific field areas or MZs, allowing for VRI.

Fertigation and Nutrient Management DSS

Elia and Conversa (2015) developed a model-based DSS for open-field vegetable production. It simulates crop growth, evapotranspiration, soil moisture, and nitrogen dynamics to determine optimal fertilizer and water applications. In principle, the model can be parameterized for MZs, allowing for VRF.

Incrocci et al. (2017) provides an overview of simulation-based DSSs for fertigation in vegetable systems. These tools integrate established crop and soil models to simulate the combined dynamics of irrigation and fertilization over time and space, enabling in-season adjustments and scenario-based planning.

Multi-Purpose DSS

Lanucara et al. (2024) developed a web-based spatial decision support system (WB-SDSS) for the automatic delineation of MZs and crop monitoring. The system is built upon an underlying SDI using open-source components such as GeoNetwork (for metadata cataloging) and GeoServer (for publishing data as OGC-compliant services like WMS, WFS, and WCS). The web-based interface, built with Bootstrap¹² and Leaflet¹³, allows users to interactively load, edit, and analyze geospatial data, execute clustering algorithms for MZ delineation, and monitor crop conditions.

2.4.6 FMIS - Farm Management Information Systems

FMIS are digital platforms that collect, organize, and process data from various agricultural operations to support farm management decisions (Sørensen et al., 2010). Modern FMIS platforms handle data from diverse farming domains – including field operations, inventory, sales and purchases, machinery use, soil mapping, and labor management (Carrer, 2023). By consolidating operational, financial, and environmental information, FMIS serve as central hubs for farm data, allowing users to monitor workflows, generate reports, and plan future actions. Fountas et al. (2015) investigated the functional scope of commercial FMIS and found that the most frequently supported features were field operations management (63%), reporting (57%), finance (45%), site-specific management (40%), inventory management (38%), machinery management (28%), and human resource management (25%). Originally designed as desktop record-keeping tools, FMIS have evolved into comprehensive cloud-based platforms for PA (Tummers et al., 2021).

FMIS have become increasingly important in PA by integrating the various components required for site-specific management. In the context of VRFI FMIS, SDI, and DSS can function as complementary components of a vertically integrated digital infrastructure. This interaction was demonstrated by Honda et al. (2014), who developed a FMIS built upon a SDI and a DSS. The SDI component was responsible for collecting and archiving sensor, weather, and remote sensing (RS) data. For decision support, the popular DSSAT¹⁴ (Decision Support System for Agrotechnology Transfer) model was employed to simulate optimal sowing dates as well as the timing and quantities of fertilizer and irrigation applications. The simulation results, along with processed RS imagery were visualized in the web-based FMIS through maps and graphical representations.

¹²<https://getbootstrap.com>

¹³<https://leafletjs.com>

¹⁴<https://dssat.net>

2.5 Suitability of the Presented Approaches

The technologies and methods presented in this chapter form the foundation for information-driven fertilization and irrigation in PA. Their suitability within the scope of this work depends on factors such as technological maturity, economic feasibility, availability, and compatibility with the overall system architecture.

For soil moisture monitoring, a stationary sensing approach was preferred over mobile or handheld systems, since continuous in-situ measurements provide timely data required to respond to rapidly changing soil moisture conditions caused by precipitation or irrigation events. FDR sensors were selected over TDR sensors. In recent years, FDR technology has reached a level of accuracy and reliability sufficient for operational agricultural applications, while still remaining less expensive than TDR systems. The lower sensor costs enabled the deployment of a denser sensing network within the field, improving the spatial representation of soil moisture variability.

For nutrient sensing, a vis-NIR multi-sensor platform was available within the project, enabling highly accurate soil property measurements with very high spatial sampling density. Consequently, the methodological approach was aligned accordingly, with a primarily sensor-based strategy focusing on soil properties rather than indirect estimation approaches based on yield or crop characteristics.

DSS approaches for fertigation range from empirical to model-based and sensor-driven methods. While model-based approaches such as *DSSAT* or *AquaCrop* offer a high level of detail, they require extensive parameterization and are often difficult to apply under operational field conditions. Sensor-driven approaches, in contrast, enable real-time decision-making but depend on reliable field instrumentation and communication infrastructure. Within this work, a sensor-based approach was selected for VR irrigation, while VR fertilization followed a hybrid approach combining sensor-derived data with empirical expertise.

With respect to spatial data management, the use of a SDI based on OGC-compliant services proves to be a suitable approach for handling heterogeneous geospatial datasets. It enables standardized data access, interoperability, and scalability, which are essential for integrating sensor data, model outputs, and application maps within a unified framework.

Regarding application technologies, not all irrigation systems are equally suited for VRFI. Stationary systems are generally too costly for implementing high-resolution VRFI over large agricultural areas. Moving systems offer the advantage that each controllable sprinkler or section traverses a larger field area, improving the economic efficiency of the often expensive VR upgrades. Within this project, a HIS was selected because, in addition to enabling VR operation, it also provides a high degree of mobility and flexibility for use across multiple fields.

Chapter 3

ADDFerti Project

3.1 Project Description

ADDFerti (A Data-Driven Platform for Site-Specific **Fertigation**) was a transnational research project funded under the ICT-AGRI-FOOD¹ ERA-NET Co-fund. The ICT-AGRI-FOOD program supports the development and adoption of digital technologies to drive the transition toward more sustainable and resilient agri-food systems. Within this framework, ADDFerti aimed to advance precision agriculture by developing an automated, ICT-based platform for variable rate fertigation (VRFI). Within the scope of ADDFerti, fertigation focused specifically on nitrogen (N) fertilization, as nitrogen represents the most critical and dynamically managed nutrient in arable crop production.

ADDFerti² (A Data-Driven Platform for Site-Specific **Fertigation**) was a transnational research project funded under the ICT-AGRI-FOOD³ ERA-NET Co-fund. The ICT-AGRI-FOOD program supports the development and adoption of digital technologies to drive the transition toward more sustainable and resilient agri-food systems. Within this framework, ADDFerti aimed to advance PA by developing an automated, ICT-based platform for VRFI. Within the scope of ADDFerti, fertigation focused specifically on nitrogen fertilization.

The project combined sensor technology, machine learning algorithms, SDIs, and a prototypical hose-reel irrigation and fertilization system to deliver site-specific fertigation at field scale. The overall goal was to improve crop yields while reducing environmental impacts through more efficient use of water and nutrients. ADDFerti ran from March 1, 2021, to August 31, 2024.

The platform followed a cloud-centric architecture, executing all core processes – including real-time data acquisition, preprocessing, modeling, and recommendation mapping – within a centralized cloud environment (Figure 3.1).

To achieve this objective, the project pursued several interrelated development goals. First (1), a robust sensor network was established, integrating proximal and remote sensing technologies to dynamically monitor soil and crop parameters. Second (2), a DSS was developed, employing advanced data fusion

¹<https://www.ictagrifood.eu/>

²<https://www.addferti.eu/>

³<https://www.ictagrifood.eu/>

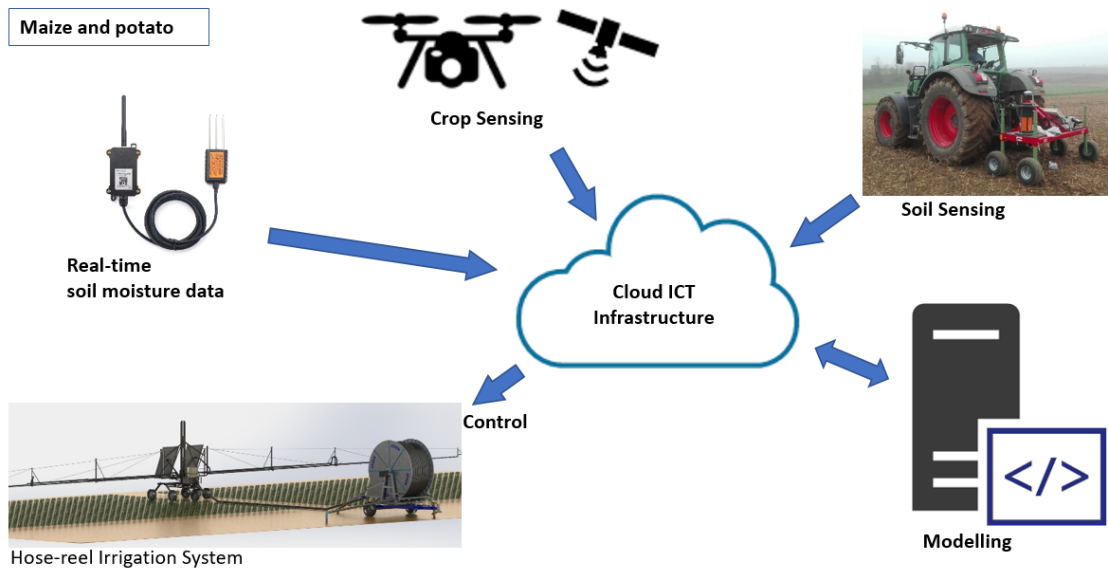


FIGURE 3.1: Technical concept of the ADDFerti platform, integrating sensors, modeling, control, and a cloud-based infrastructure.

techniques to generate VRFI recommendations tailored to site-specific conditions. Third (3), a cloud-based SDI was implemented to support real-time data ingestion, processing, visualization, and dissemination through a dedicated geoportal. In parallel (4), a novel hose-reel fertigation machine was prototyped, equipped with four independently controllable zones for irrigation and fertilization. This system was designed to autonomously execute application maps generated by the DSS. The integrated solution was subsequently validated (5) through field trials on commercial farms in Turkey, Germany, and Belgium. Finally (6), knowledge transfer and stakeholder engagement formed essential components of the project. Targeted dissemination activities, including workshops and pilot demonstrations, were conducted to promote awareness and encourage adoption among farmers, industry partners, and policymakers.

3.1.1 Project Partner

The ADDFerti project was a collaborative effort involving six international partners from five European countries:

- **Ghent University (UGent), Belgium:** Project coordinator, responsible for soil sensing, MZ delineation, and conducting local field experiments.
- **Aristotle University of Thessaloniki (AUTH), Greece:** Developed machine learning models to enhance the accuracy of VRFI recommendations.
- **Bursa Uludag University (BUÜ), Turkey:** Oversaw the prototyping of the HIS and conducted local field experiments.

- **Rostock University (RU), Germany:** Led the development of the ICT infrastructure, including the sensor network, cloud-based geoportal, and DSS; also conducted local field trials.
- **Quantis (QUA), Switzerland:** Performed environmental and economic impact assessments using Life Cycle Analysis (LCA) and Cost-Benefit Analysis (CBA).
- **Sezer Inc., Turkey:** Industrial partner responsible for mechanical and hydraulic modifications of the HIS.

3.1.2 Work Packages

The ADDFerti project was organized into eight work packages (WPs), each addressing a specific component of the integrated VRFI solution.

WP1 – Sensing focused on monitoring and mapping of the experimental fields, including the development and deployment of LoRaWAN-based soil moisture sensor networks, soil property mapping using a vis-NIR multi-sensor platform, as well as crop monitoring via UAV and satellite data and yield mapping. **WP2 – Modelling** addressed spatial modeling, including the delineation of MZs and the development of machine learning-based approaches. **WP3 – ICT and Data Management** involved the development of a cloud-based SDI, the definition and implementation of APIs, and the embedding of fertigation logic into a DSS. **WP4 – Control** focused on the mechanical and hydraulic adaptation of a HIS to enable VRFI. **WP5 – Implementation** comprised the field-scale deployment and testing of the integrated system at pilot sites. **WP6 – Impact Evaluation** assessed environmental and economic outcomes through life cycle assessment (LCA) and cost-benefit analysis (CBA). **WP7 – Dissemination, Exploitation and Communication** facilitated stakeholder engagement and knowledge transfer through workshops, social media, and digital outreach. **WP8 – Project Management** covered project management, deliverable tracking, and compliance with funding requirements.

3.1.3 Funding

The ADDFerti project was funded under the ICT-AGRI-FOOD ERA-NET Co-fund, a European initiative aimed at promoting the use of digital technologies to support the transition toward more sustainable, resilient, and secure agri-food systems. With financial support from the European Commission, ICT-AGRI-FOOD coordinates annual transnational research calls to foster innovation and cooperation across EU Member States and associated countries. National funding for the ADDFerti project was provided by the following agencies: Fonds Wetenschappelijk Onderzoek (FWO, Belgium), General Secretariat for Research and Innovation (GSRI, Greece), The Scientific and Technological Research Council of Turkey (TUBITAK), Bundesministerium für Bildung und Forschung (BMBF, Germany), and the Federal Office for Agriculture (Switzerland).

3.2 Description of Test Sites in Germany, France, and Turkey

The field experiments within the ADDFerti project were conducted on three commercial test sites located in Germany, France, and Turkey, representing different soil types, climates, and topography.

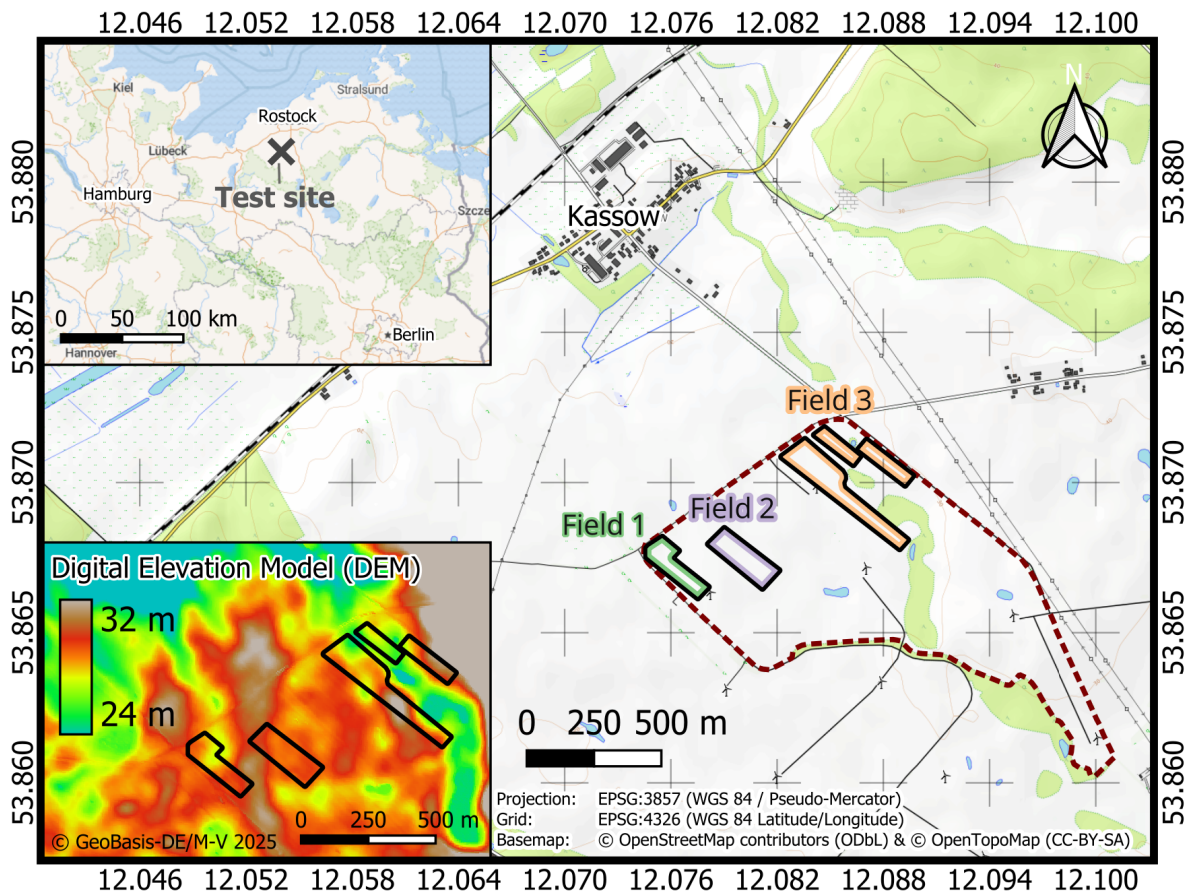


FIGURE 3.2: Location of the study site in Kassow, Germany.

3.2.1 Kassow, Germany

The German test site is located in Kassow (53.868°N, 12.083°E), approximately 30 km from the Baltic coast in northeastern Germany, with Rostock as the nearest city (Figure 3.2). The region has a temperate maritime climate, with winter temperatures ranging from 0 to 4 °C and summer temperatures averaging between 17 and 22 °C. Annual precipitation typically ranges between 600 mm to 700 mm, with slightly higher values during the summer months. According to the Köppen climate classification, the site falls under category Cfb (temperate oceanic climate). The soils are predominantly sandy to loamy sand, and the topography is slightly hilly due to ground moraine formations from the Weichselian glaciation. A drainage system is in place to ensure field accessibility during wetter seasons.

The experimental area is part of a 100 ha arable field. For the ADDFerti trials, three subfields were delineated, totaling approximately 10 ha. The boundaries of Field 1 (1.5 ha) and Field 3 (6.7 ha) were shaped by the spatial constraints of the HIS, local topography, and water supply infrastructure. Field 2 (2.0 ha) was equipped with a center-pivot irrigation system and served as a reference plot. During the 2022 growing season, all three subfields were cultivated with potatoes and used as test areas for soil, crop and yield sensing, as well as for the generation of VR application maps.

3.2.2 Les Moères, France

The test sites of UGent are located in Les Moères (51.014°N, 2.549°E) in France near the French-Belgian border, approximately 10 km east of Dunkirk (Figure 3.3). The region has a temperate oceanic climate (Cfb in the Köppen classification), with cool to mild winters and warm summers. Mean annual temperatures range from 6 to 10 °C, and annual precipitation typically lies between 700 mm and 850 mm. The topography is flat, with negligible relief. The soil texture of the experimental fields was classified as sandy loam, based on the texture-by-feel method conducted by the Soil Service of Belgium (Heverlee, Belgium). All fields were cultivated with potatoes. Soil, crop, and yield sensing, as well as VR map generation and field experiments, were conducted in 2023 on the 'Blondel-3' field (7 ha), and in 2024 on the nearby fields 'Gallou Tiboult' (12 ha), 'Grandplane' (12 ha), and 'Mortier' (11 ha).

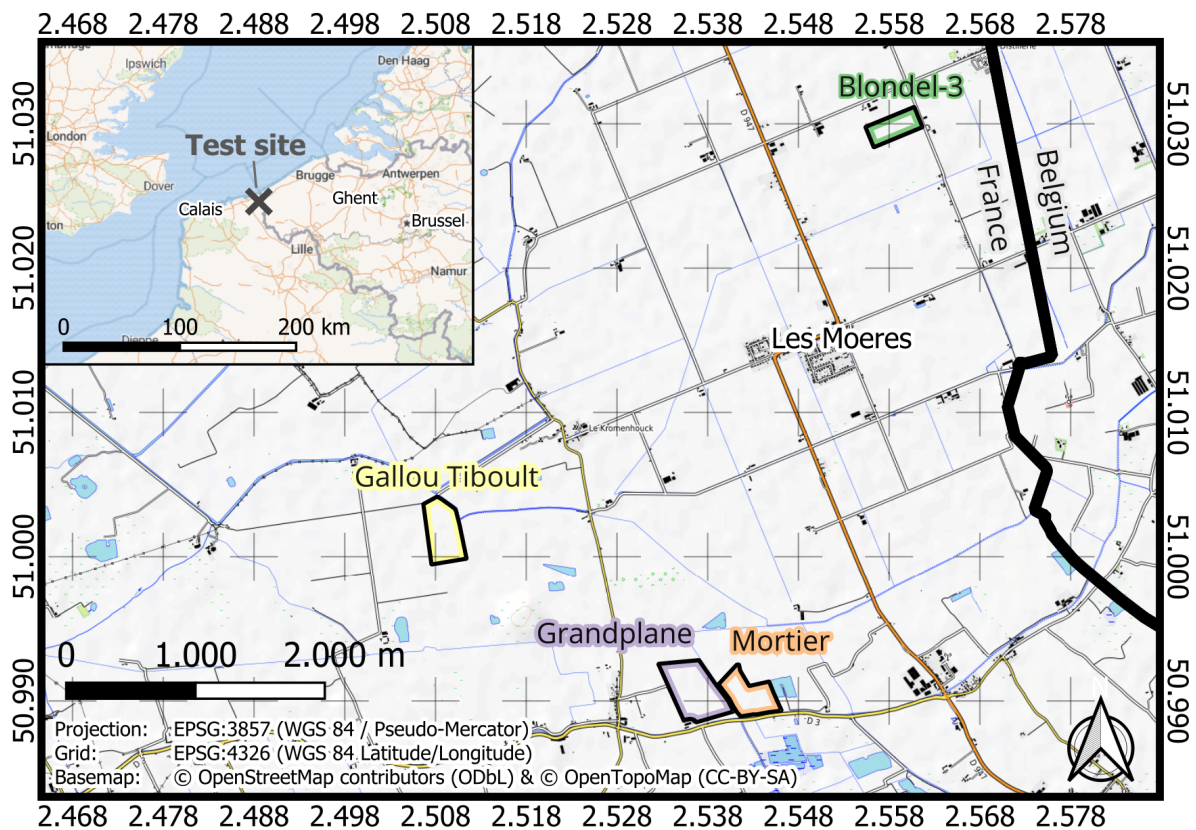


FIGURE 3.3: Location of the study site in Les Moeres, France.

3.2.3 Karacabey, Turkey

The Turkish test site (Figure 3.3) is located on a commercial farm in Karacabey, approximately 50 km west of Bursa (40.0822°N, 28.2258°E). The region has a Mediterranean climate, classified as Csa under the Köppen system, with hot, dry summers from June to September and cool, damp winters that account for the majority of annual precipitation. The topography is flat, with negligible relief. The soil texture of the experimental fields varies between sandy clay and loamy clay.

Three fields in close proximity were selected for testing: Field 1 (10 ha), Field 2 (3 ha), and Field 3 (7 ha). All fields were cultivated with maize. Soil, crop and yield sensing, VR map generation, and field experiments were conducted in 2022 for Field 1 and Field 2, and in 2023 for Field 3. The Turkish site served as the primary test bed for implementing and evaluating the HIS, with Field 3 being the only location where a full VRFI application was carried out under operational field conditions in August 2023.

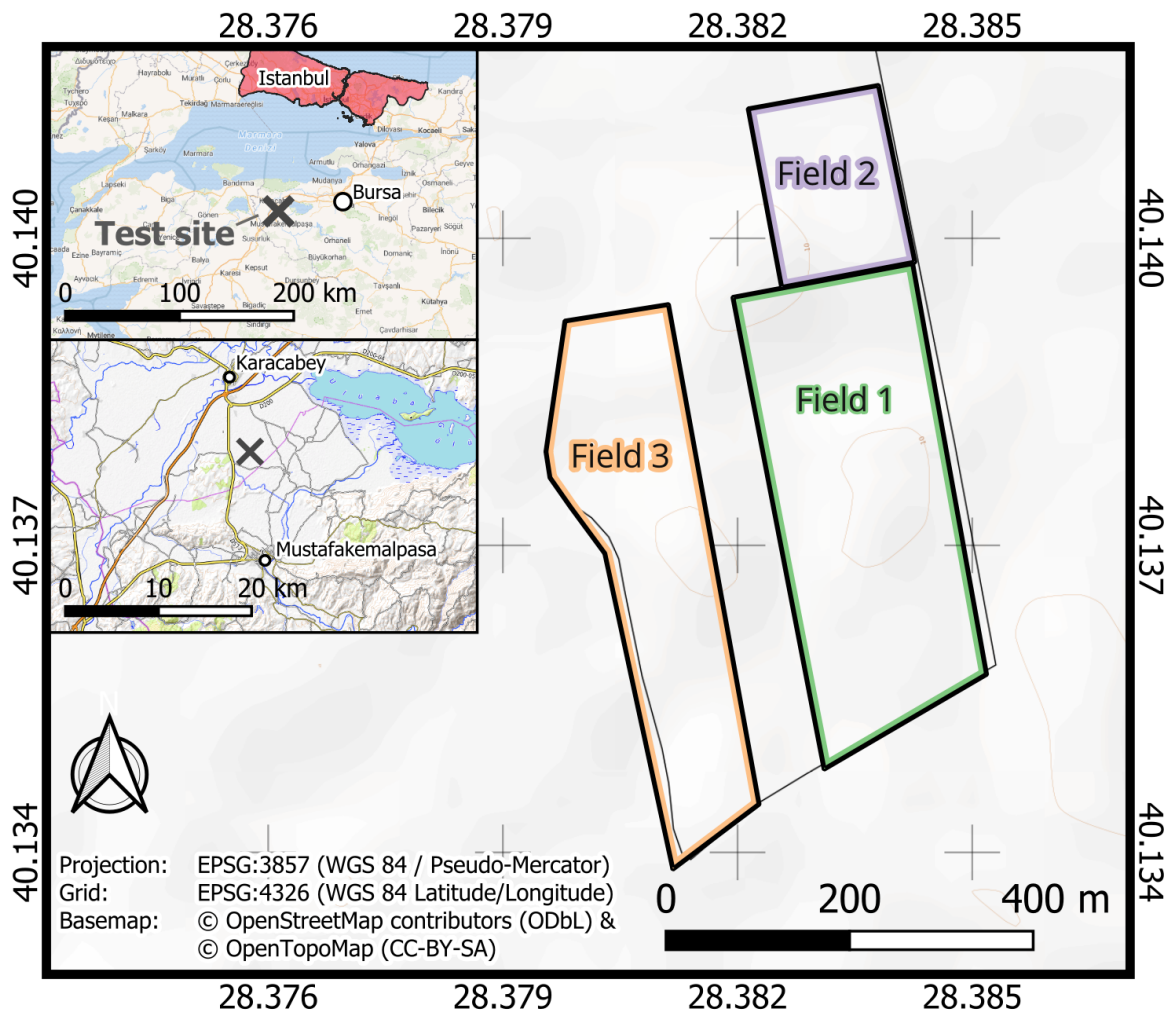


FIGURE 3.4: Location of the study sites in Karacabey, Turkey.

Chapter 4

Sensor Technology for Soil and Crops in ADDFerti

Accurate soil and crop sensing is essential for developing site-specific irrigation and fertilization prescriptions. Within the ADDFerti project, a variety of sensor systems were deployed across the test sites. This chapter presents the sensor technologies used in the project, including a LoRaWAN-based soil moisture sensor network, a vis-NIR multi-sensor soil scanning platform for soil property mapping, and several crop sensing approaches – ranging from satellite and UAV-based imagery to handheld NDVI sensors. The chapter concludes with a critical evaluation of the Stenon FarmLab, a novel handheld soil sensor.

4.1 LoRaWAN Soil Moisture Sensor Network: Design and Application

A cloud-based soil moisture sensor network was established by RU to enable real-time monitoring of soil water status, providing a key input for the generation of irrigation recommendation maps. The network was implemented via local LoRaWAN infrastructures at the experimental sites in France, Germany, and Turkey.

4.1.1 Soil Moisture Sensors

As soil moisture sensors, Dragino LSE01 units (Shenzhen, China) were employed (Figure 4.1). The LSE01 is a LoRaWAN-based IoT sensor that measures soil moisture content (MC), soil temperature, and electrical conductivity (EC), transmitting the data via LoRaWAN. The sensors determine MC using frequency domain reflectometry (FDR), with compensation for soil temperature and conductivity. The specifications provided by the manufacturer are summarized in Table 4.1. Further features of the LSE01 include compliance with LoRaWAN 1.0.3 Class A, operation in the EU868 frequency band, an IP66-rated waterproof enclosure, downlink capability for configuration changes, and an 8500 mA h Li-SOCl₂ battery that enables long-term operation of up to ten years according to the manufacturer. The sensors are factory-calibrated for mineral soils and suitable for use in saline-alkali and loamy soils.

Each LSE01 sensor is equipped with its own LoRaWAN-compatible processing unit and transmitter, as well as a unique set of keys for LoRaWAN registration.

TABLE 4.1: Manufacturer specifications of the Dragino LSE01 soil moisture sensor.

	Soil Moisture	Soil Conductivity	Soil Temperature
Range	0–100.00%	0–20000 $\mu\text{S}/\text{cm}$	-40.0°C–85.0°C
Resolution	0.01%	1 $\mu\text{S}/\text{cm}$	0.01°C
Accuracy	$\pm 3\%$ (0–53%) $\pm 5\%$ (>53%)	$\pm 2\%$ FS ¹	$\pm 0.3^\circ\text{C}$ (10–50°C) <0.6°C (all other)
Method	FDR with temperature compensation	Conductivity with temperature compensation	RTD (Resistance Temperature Detector)

¹ FS = Full Scale. An accuracy of $\pm 2\%$ FS means the error is calculated as a percentage of the full measurement range



FIGURE 4.1: Dragino LSE01 soil moisture sensors installed in the field in Kassow, Germany.

Once registered in a local LoRaWAN network, the sensor automatically connects and begins periodic uplink data transmission at 20 min intervals.

4.1.2 Solar Powered LoRaWAN Gateway

The local LoRaWAN network was provided by a Dragino DLOS8 Gateway. The DLOS8 is an open-source outdoor LoRaWAN gateway that bridges a LoRa wireless network to an IP network via WiFi, Ethernet, or 3G/4G LTE cellular.

At the German test site, no grid power source was available in the vicinity. Therefore, a solar station to power the DLOS8 Gateway was deployed (see Figure 4.2). The configuration included the following components:

- **80W solar module.**
- **50Ah 12V battery** to store power for nighttime or periods of low sunlight.
- **12V charge controller** to protect the battery from overcharging or deep discharge.

- **3 dbi Antenna** mounted at 6 m height to extend the range of the LoRaWAN network.
- **LTE SIM card** for internet connectivity, enabling data transmission to the ADDFerti geoportal.

This configuration ensured a stable and autonomous power supply, supporting continuous data collection and transmission of the soil moisture sensor data.

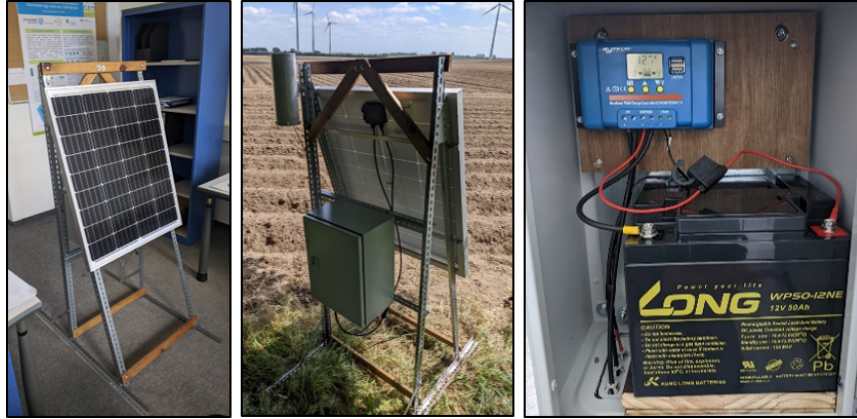


FIGURE 4.2: Solar-powered station for the DLOS8 LoRaWAN Gateway at the Kassow test field in Germany. The gateway unit is mounted on the solar rack.

4.1.3 Workflow for Retrieving Soil Moisture Data

This section describes the workflow for transferring soil moisture data from the field to the ADDFerti cloud infrastructure. The data flow is illustrated in Figure 4.3.

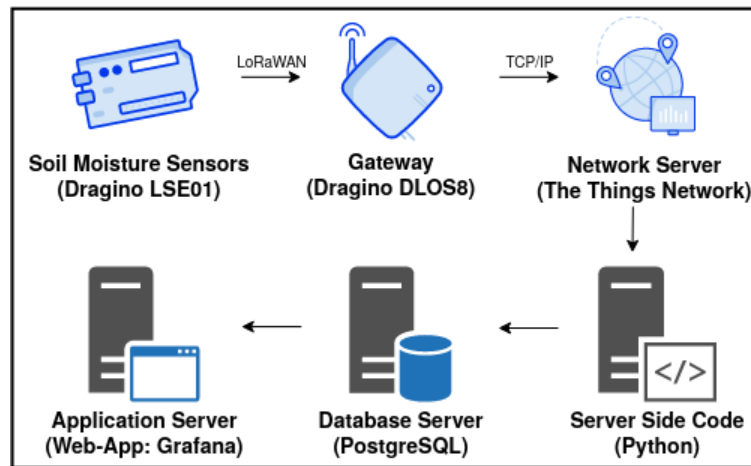


FIGURE 4.3: The data flow from the in-field soil moisture sensors via LoRaWAN and the network server to the ADDFerti cloud platform and dashboard.

In addition to the sensors, the gateway, and the ADDFerti server, the workflow required a network server to manage device registrations, authenticate connections, and route LoRaWAN messages. For this purpose, The Things Network¹

¹<https://www.thethingsnetwork.org>

(TTN) was employed – an open-source, community-driven LoRaWAN network server that provides device management, secure data routing, and open APIs for data access. TTN also offers access to a network of free public LoRaWAN gateways, which provide good coverage in many parts of Western Europe², although not at the ADDFerti test sites.

The LSE01 sensors periodically transmit messages via LoRa to the DLOS8 Gateway every 20 minutes. The gateway decodes the LoRa chirps into hexadecimal format and enriches the payload with metadata. These packages are then forwarded to the TTN server, where the data is decoded into JSON format and temporarily stored (up to 24 hours). The decoding is performed using a JavaScript decoder provided in the Dragino manual.

A Python script running on the ADDFerti server retrieved the data from the TTN server via its API. The script parsed the JSON, transformed the content into a relational table, and appended the records to a PostgreSQL database hosted on the ADDFerti server. The code for this adapter is available at: https://github.com/alexsteiger/TTN_Adapter.

In addition, the live sensor data was published on a dedicated web dashboard for real-time monitoring. From there, the data could also be downloaded as a CSV file or accessed via an API in JSON format. The dashboard was implemented using the open-source software Grafana³, which enables flexible data visualization through customizable panels, including interactive maps, charts, and tables (Figure 4.4). The ADDFerti dashboard was deployed as a web application⁴.



FIGURE 4.4: Grafana dashboard for the Kassow test field in Germany, displaying sensor locations (left), soil MC time series for each sensor (center), and the local weather forecast (right).

In France, Germany, and Turkey, the LoRaWAN soil moisture sensors were installed shortly after crop planting and removed before harvest. Placement of the LSE01 sensors was aligned with the delineated MZs, ensuring that each MZ was represented by at least one sensor (Figure 4.5). As an example, Figure 4.6 illustrates four months of soil MC measurements from the 2023 potato field in Kassow, Germany. The results highlight substantial differences in MC,

²<https://ttnmapper.org/heatmap/>

³<https://grafana.com>

⁴<https://sensor.addferti.eu>

primarily driven by variations in clay content, topography, and installation depth.



FIGURE 4.5: Locations of LoRaWAN soil moisture sensors in the Kassow test field, Germany, shown in relation to the delineated irrigation MZ.

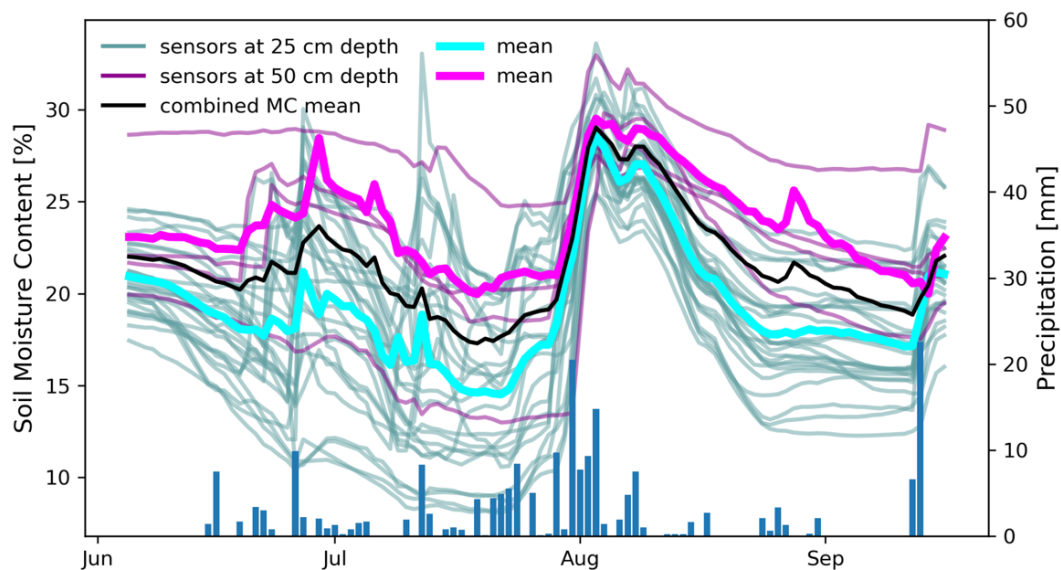


FIGURE 4.6: Soil MC measured over four months in 2023 with 30 Dragino LSE01 sensors in the Kassow potato field, highlighting variability by location and depth.

Before the field trials and equipment acquisition, the workflow was validated using a low-cost Arduino sensor equipped with a LoRa module, as reported in Steiger (2022)⁵.

⁵Available at: https://archiv.geomv.de/geoforum/2022/doc/Tagungsband_GeoForum-MV-2022_eBook.pdf#page=71

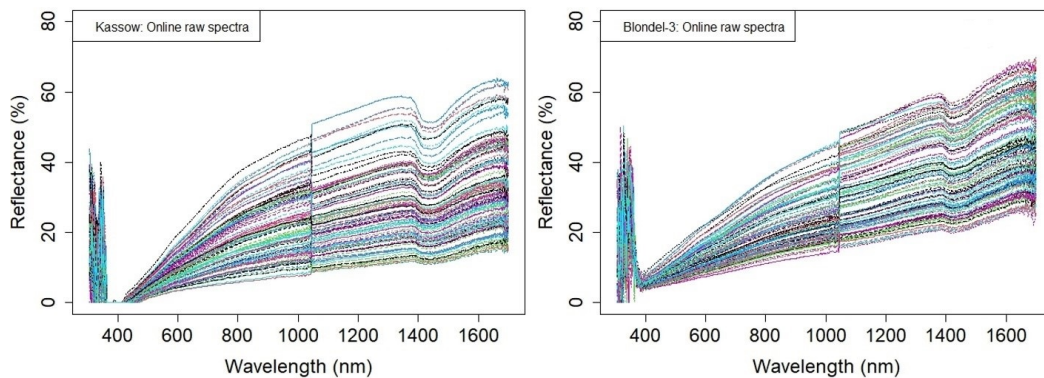


FIGURE 4.7: 100-online raw spectra collected in Kassow, Germany and Blondel-3 in France as an example.

4.2 vis-NIR Multi-Sensor Soil Scanning Platform: Description and Field Implementation

For soil sensing, a multi-sensor platform developed by Mouazen and Ramon (2006) and provided by UGent was used to perform on-line visible and near-infrared (vis-NIR) spectroscopy across all test fields. The resulting soil maps served as the primary data input for generating irrigation and fertility MZs.

The multi-sensor platform is mounted on a tractor's three-point linkage and equipped with a subsoiler designed to create a trench at an adjustable depth between 15 cm and 25 cm (see Figure 4.8). Affixed to the heel of the subsoiler chisel is an optical probe connected to a vis-NIR spectroscopy sensor (CompactSpec Tec5 Technology, Steinbach, Germany), covering a spectral range from 305 nm to 1700 nm at a resolution of 1 nm (see Figure 4.7). Calibration references are maintained using a 100 % ceramic disc, with scans conducted every 30 minutes. The platform is further equipped with a Differential Global Navigation Satellite System (DGNSS; Trimble CFX-750) and a laptop running MultiSpec Pro-II software to record both soil spectra and GNSS data at a frequency of 1 Hz.

The vis-NIR platform enables the estimation (prediction) of a broad set of soil properties, including phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), cation exchange capacity (CEC), pH, soil moisture content (MC), clay content, and total organic carbon (TOC).

Parallel to the on-line scanning, soil samples are collected at random intervals from the bottom of the trenches created by the subsoiler. Each sample is georeferenced to the corresponding vis-NIR reading, typically within a few centimeters of the scanning point. The samples are air-dried, homogenized, and visible debris such as crop residues, roots, and stones is removed. Each sample is reduced to approximately 150 g and analyzed in the laboratory for soil properties and nutrient contents. Furthermore the samples are scanned with a laboratory vis-NIR spectrometer to enable the development of regression



FIGURE 4.8: The on-line vis-NIR multi-sensor platform developed by Mouazen and Ramon (2006) on the field in Kassow, Germany in August 2022 (left). The vis-NIR sensor is located on the heel of the subsoiler (right).

models for predicting soil properties from the field-collected spectra. If not already available, the collected soil samples also allow for the determination of hydraulic soil parameters such as field capacity (FC), permanent wilting point (PWP), and soil bulk density. These parameters are required at a later stage for the calculation of irrigation rates.

The creation of regression models involves dividing the dataset into a calibration set (70 %) and a validation set (30 %). Partial least squares regression (PLSR) with cross-validation is applied to the calibration set, and the resulting models are validated by comparing predicted against measured laboratory values. Model accuracy is evaluated using the coefficient of determination (R^2), root mean square error of prediction (RMSEP), residual prediction deviation (RPD), and the ratio of performance to interquartile distance (RPIQ).

After validation, the prediction dataset, including GNSS coordinates, is used to generate spatially continuous maps of soil properties. Interpolation methods such as inverse distance weighting (IDW) and ordinary kriging (OK) are employed to capture spatial heterogeneity. These maps provide the basis for delineating MZs and informing fertigation recommendations within the ADDFerti DSS.

The results of soil scanning for the fields in France (Blondel-3), Germany (Kassow Field 1, 2 and 3), and Turkey (Field 1 and 2) are published in Qaswar et al. (2024), Steiger et al. (2025), and Bantchina et al. (2024) respectively. In these publications the process for the development of calibration models and delineation of MZs is also described in more detail. For the Kassow test field in Germany, the resulting soil maps are shown in Figure 4.9; here, interpolation was carried out using ordinary kriging with fitted semivariograms.

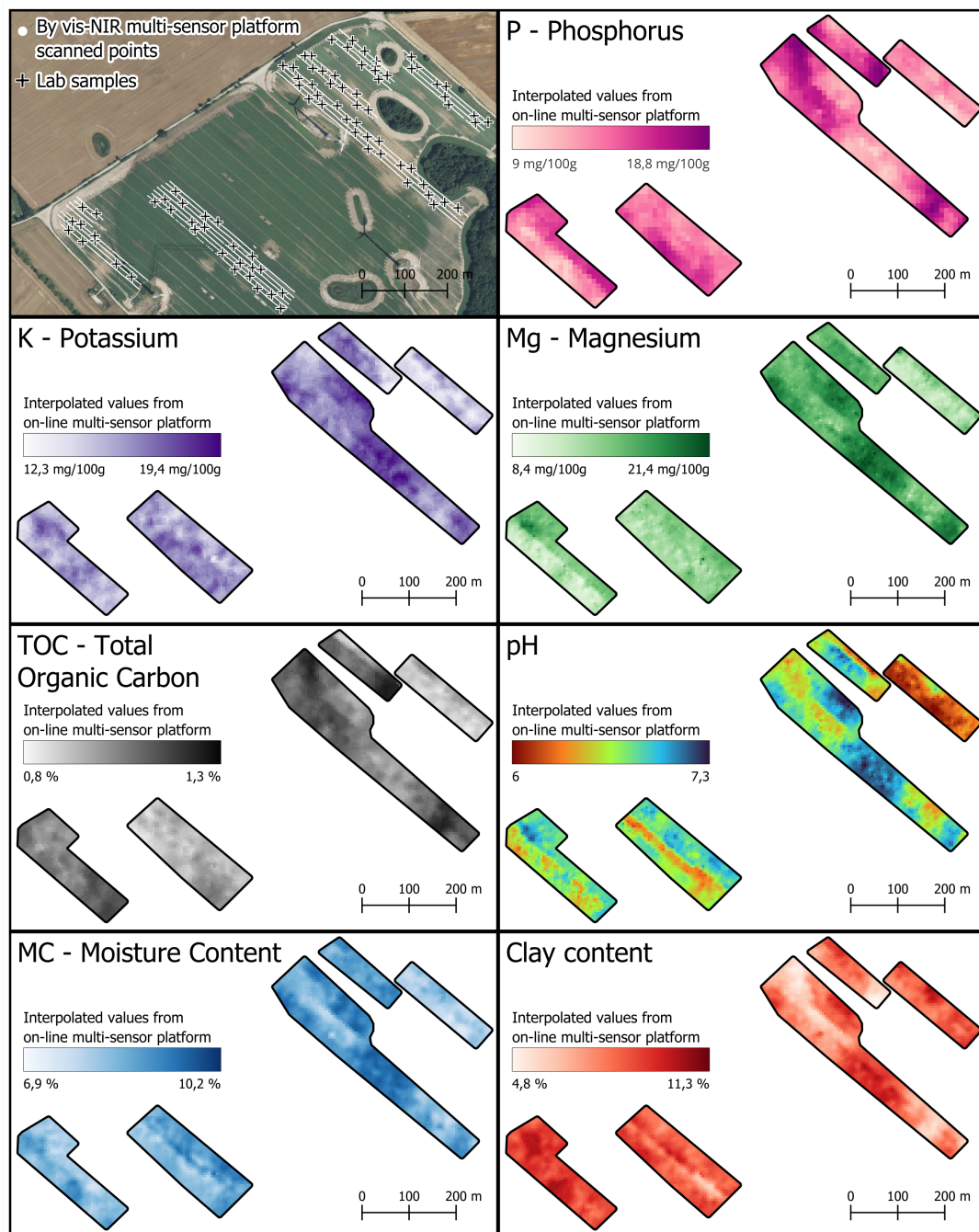


FIGURE 4.9: Interpolated soil property maps for the Kassow test field in 2022, derived from vis-NIR multi-sensor platform measurements. Source: Steiger et al. (2025).

4.3 Crop Sensing Solutions

In ADDFerti, different crop sensing approaches were employed at the test sites, depending on sensor availability and site conditions.

At the Kassow test site in Germany, UAV flights equipped with a multispectral sensor (vis and NIR) were conducted during the 2023 growing season. The UAV data additionally enabled the estimation of crop height and canopy

cover. In Turkey, the SpectroSense SKL925 handheld sensor (Skye Instruments, Llandrindod Wells, UK) was used to collect NDVI measurements in Field 1 and 2. The SKL925 includes an integrated GNSS unit for georeferencing the recordings. Across all test sites, Sentinel-2 satellite imagery was used by RU to calculate NDVI and NDRE at 10 m spatial resolution. The Sentinel-2 data were retrieved and processed via Google Earth Engine⁶ to enable automated calculation of vegetation indices. These crop sensing datasets were subsequently integrated with soil sensing data to support MZ delineation.

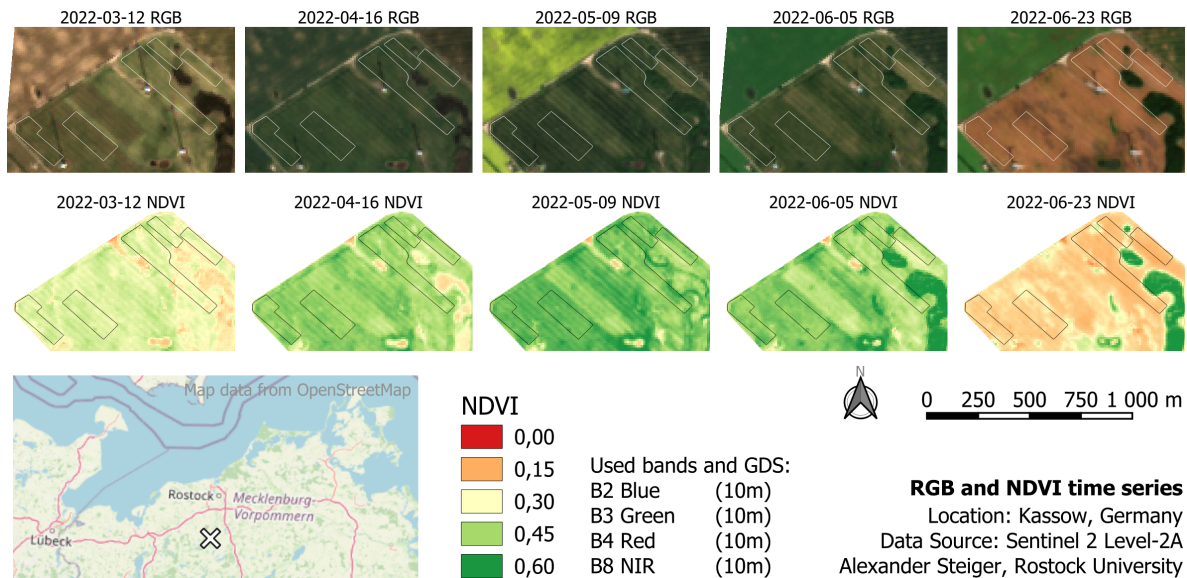


FIGURE 4.10: NDVI time series for the Kassow field, Germany, derived from Sentinel-2 imagery on five dates during the 2022 growing season.

4.4 Alternative Sensing Approaches: Experiences with the Stenon FarmLab

The adaptation of novel sensing technologies is essential in PA, as many applications – such as the generation of fertigation recommendation maps – are only as reliable as the quality of the underlying data. However, obtaining high-resolution soil data can at the same time be costly and time-consuming, limiting its accessibility for farmers.

One promising tool addressing this challenge is the Stenon FarmLab, a handheld soil sensor that provides immediate, in-field measurements without the need for laboratory analysis. This section provides the results of a study done at the test site in Kassow, Germany, which assessed the accuracy and practical usability of the Stenon FarmLab by comparing its performance with the vis-NIR multi-sensor soil sensing platform (Steiger et al., 2025)⁷.

⁶<https://earthengine.google.com/>

⁷Available at: <https://www.sciencedirect.com/science/article/pii/S2772375524003216>

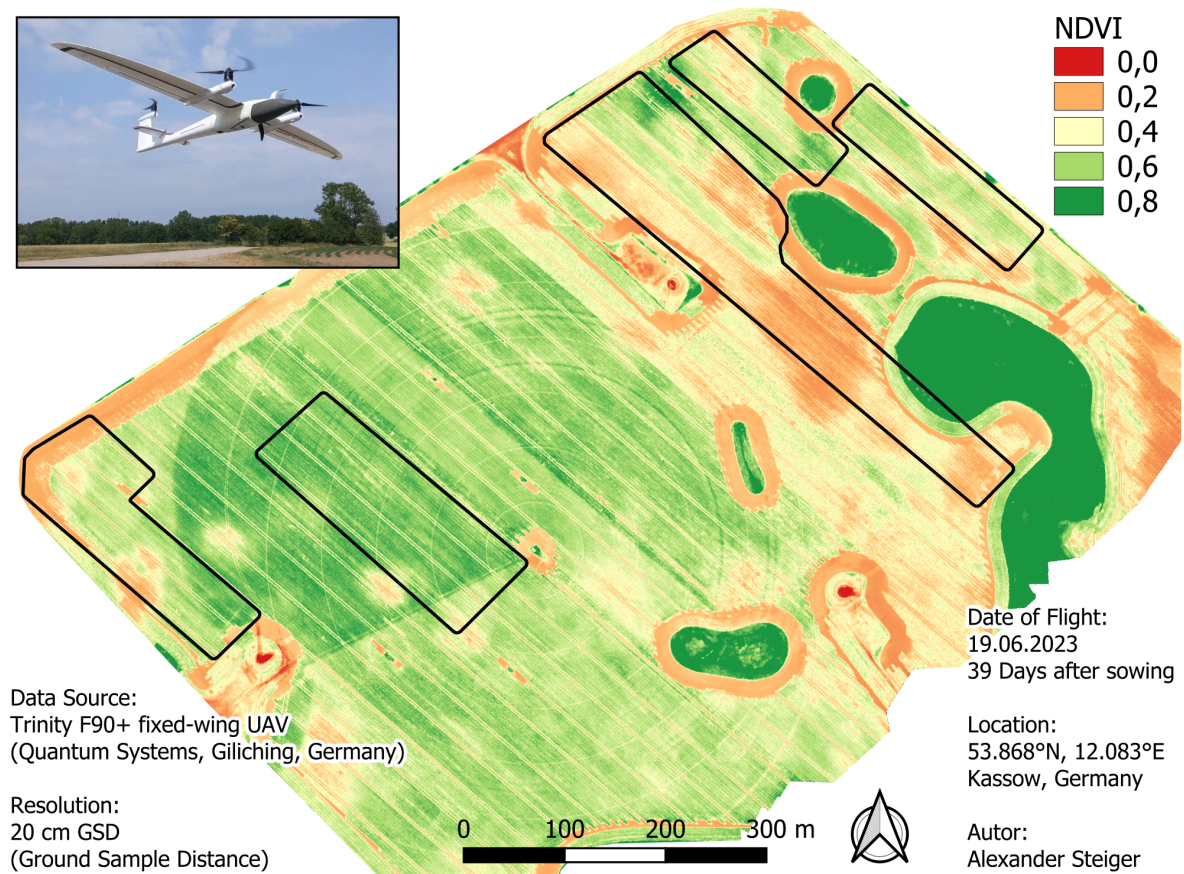


FIGURE 4.11: High-resolution NDVI map of the Kassow test field, acquired with an Trinity F90+ (Quantum-Systems, Gilching, Germany) fixed-wing UAV on 19 June 2023.

Experimental Setup and Methodology

The Stenon FarmLab is a sensor-equipped handheld spade designed to provide real-time soil analysis directly in the field. It combines impedance and spectral measurements across the UV to NIR range to estimate soil parameters such as N, P, Mg, Ca, SOC (soil organic carbon), pH, texture, temperature, and MC (Stenon GmbH, 2025). Measurements are automatically georeferenced via an integrated GNSS sensor and transmitted via the internet to a server-based platform for access and visualization.

The experiments were conducted on Field 1, 2 and 3 of the field in Kassow, Germany (see Figure 3.2). Soil sensing was performed using both technologies at different time intervals. The vis-NIR multi-sensor platform collected on-line soil data in August 2022, while the Stenon FarmLab was used for monthly soil sampling from November 2022 to September 2023. Due to the time gap between these measurements, only the more time-stable soil properties were considered for correlation analysis.

The vis-NIR sensor data were calibrated and validated using laboratory analyses and PLSR, as described in Section 4.2. The vis-NIR platform demonstrated high accuracy in soil property estimation, with calibration R^2 -values ranging

from 0.68 to 0.97 and validation R^2 -values between 0.64 and 0.88. Based on this, high-resolution soil property and nutrient maps were generated, capturing spatial heterogeneity within the field (see Figure 4.9).

In contrast, the Stenon FarmLab exhibited substantial variability in measurement accuracy and consistency. Correlation analyses between the two systems for time-stable soil properties revealed only limited agreement (see Figure 4.12 and 4.13). For soil organic carbon (SOC), the coefficient of determination was $R^2 = 0.29$, for pH it was $R^2 = 0.41$, and for soil texture $R^2 = 0.50$. Furthermore, unrealistic temporal trends were detected for $N_{\min}$, SOC, and pH, which could not be explained by known soil processes or management practices.

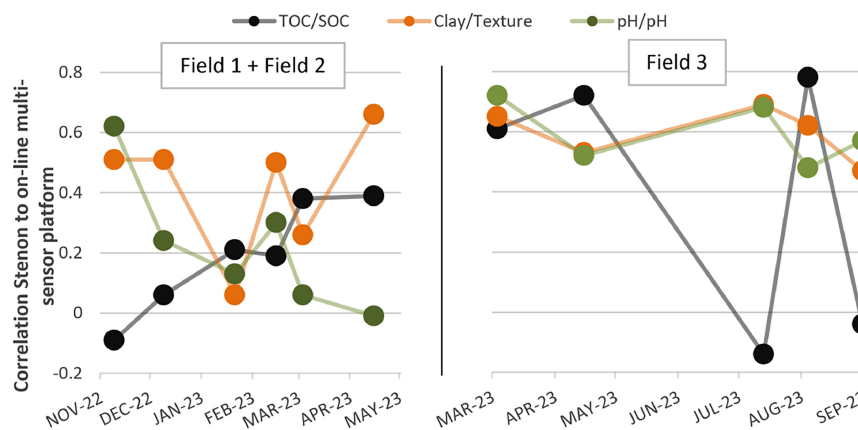


FIGURE 4.12: Correlation of Stenon FarmLab measurements with vis-NIR multi-sensor platform results for the Kassow test fields. Displayed are the found R^2 -values for SOC, pH, and soil texture. Source: Steiger et al. (2025).

Similar studies have reported poor to moderate accuracy of the Stenon FarmLab across several soil parameters (Vikuk et al., 2024; Olfs et al., 2023). The results of this study fall within a similar range and, in some cases, slightly outperform those earlier evaluations. Grenzsdörffer et al. (2025) further investigated the sensor's accuracy at six different sites near Rostock, Germany, including the Kassow samples from Steiger et al. (2025). Their findings confirmed that parameters such as $N_{\min}$, phosphorus, and SOC exhibited poor temporal stability and low spatial correlation, with soil texture emerging as the most reliable parameter.

These findings suggest that although the Stenon FarmLab offers clear advantages in terms of usability and immediacy, its measurement accuracy is insufficient to serve as a dependable alternative to established soil sensing technologies.

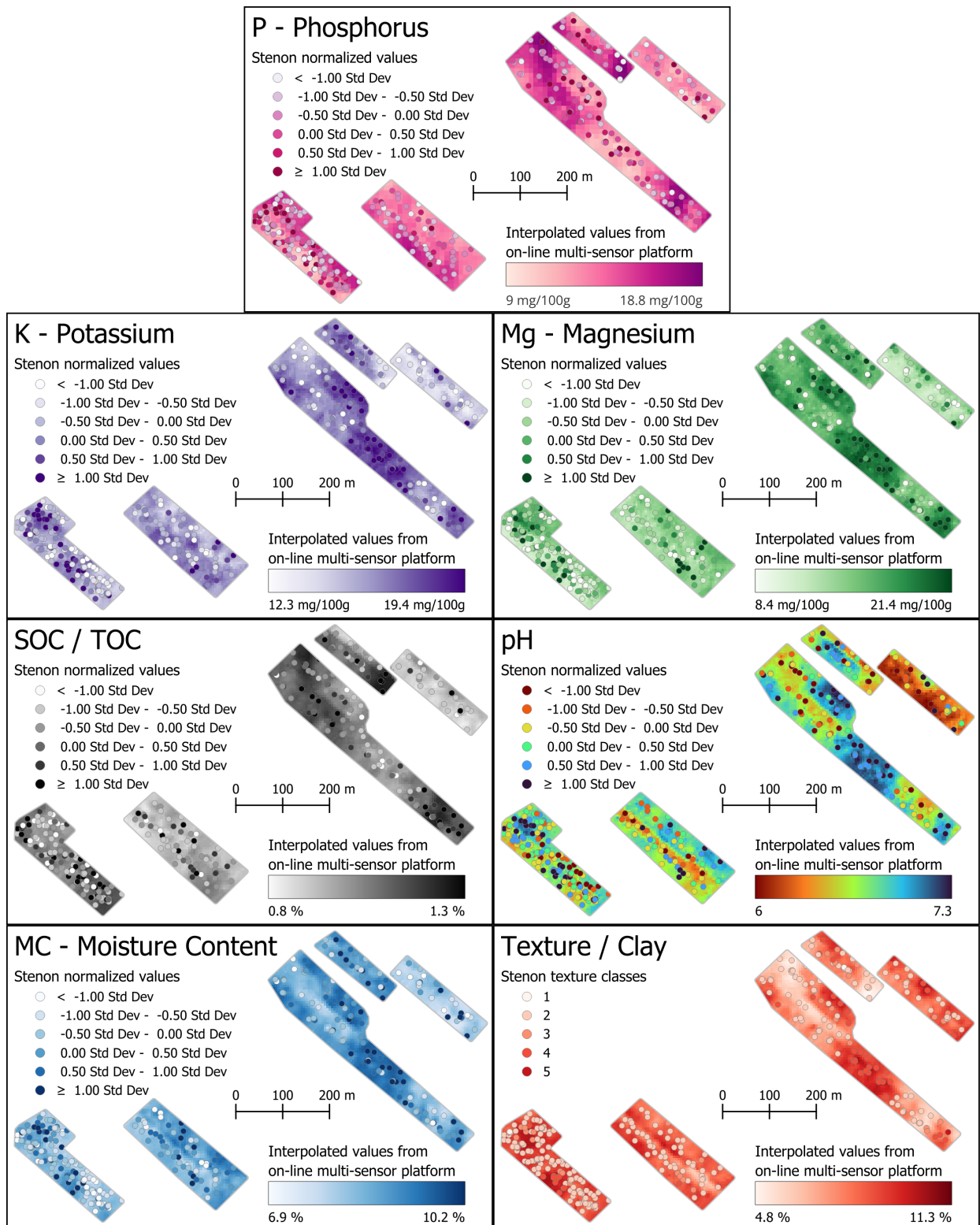


FIGURE 4.13: The normlized Stenon FarmLab results, with the on-line predictions underlaid as continuous soil maps. Source: Steiger et al. (2025).

Chapter 5

Development of a Spatial Data Infrastructure for ADDFerti

A central component of the ADDFerti project was the development of a SDI to support the acquisition, management, exchange, and visualization of geospatial data from multiple sources. This infrastructure, developed by RU, served as the backbone for integrating heterogeneous datasets – ranging from in-field sensor measurements and laboratory analyses to model outputs and fertigation application maps – into a coherent, accessible system.

At its core, the SDI comprised a GeoNode-based geoportal for data storage, cataloging, and publication, complemented by a set of automated data pipelines enabling bidirectional exchange between the geoportal and other project components. These pipelines handled both the ingestion of new data (e.g., sensor readings, weather forecasts) and the distribution of processed outputs (e.g., application maps) to decision support tools and field machinery.

The overall information flow and system architecture, including the interactions between sensors, the SDI, the decision support system (DSS), and the hose-reel irrigation system (HIS), are shown in Figure 5.1.

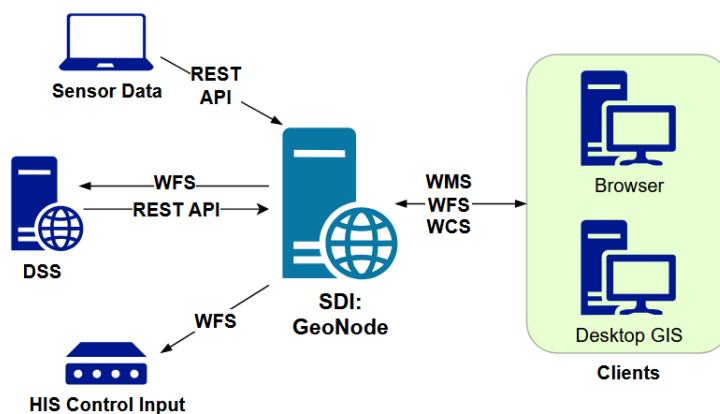


FIGURE 5.1: System architecture of the ADDFerti ICT platform, illustrating the interfaces between sensors, SDI, DSS, and field machinery.

5.1 GeoNode-Based Geoportal: Design, Features, and Role

The ADDFerti geodata portal was built using GeoNode as a framework. GeoNode is an open-source geospatial content management system designed for the management and publication of geospatial data. GeoNode was chosen due to its seamless integration of geospatial data storage, metadata cataloging, and standardized web services, along with its intuitive user interface.

The platform enables the unified creation and management of datasets, metadata, access rights, and interactive maps within a single environment. Moreover, GeoNode is highly extensible, offering a modular architecture that allows for its integration with external applications and services, as well as customization by software developers to meet project-specific requirements.

Figure 5.2 illustrates the core components of the GeoNode framework as implemented in ADDFerti. GeoNode is primarily developed in Python and JavaScript, using Django¹ as the web framework and nginx² as the web server. The spatial data services are provided by a dedicated instance of GeoServer³, which handles the rendering and delivery of geospatial data through OGC-compliant services such as WMS, WFS, and WCS.

GeoServer acts as the backbone for publishing both vector and raster datasets stored in the spatial database. It provides styling, tiling, reprojection, and service endpoints that are consumed by the GeoNode frontend or external clients. In the ADDFerti implementation, PostgreSQL⁴ was used as the database backend, extended with the PostGIS⁵ module to enable spatial data types and functions. Raster datasets are stored in a file system.

Metadata management is handled through the Catalogue Service for the Web (CSW), which allows querying and harvesting of geospatial metadata records. By default, GeoNode integrates pycsw⁶ as the CSW service implementation. To optimize performance when serving large datasets or complex map compositions, GeoWebCache⁷ is employed to pre-render and cache map tiles. This significantly reduces server load and improves response times for frequently accessed layers.

GeoNodes browser-based interface (see Figure 5.3) offers a comprehensive suite of features for managing, sharing, and interacting with spatial data through. Users could upload a wide range of geospatial formats, including vector data (e.g., Shapefile, GeoJSON, GeoPackage) and raster data (e.g., GeoTIFF), as well as tabular data (e.g., CSV). Upon upload, each dataset

¹<https://www.djangoproject.com>

²<https://nginx.org>

³<https://geoserver.org>

⁴<https://www.postgresql.org>

⁵<https://postgis.net>

⁶<https://pycsw.org>

⁷<https://geowebcache.osgeo.org>

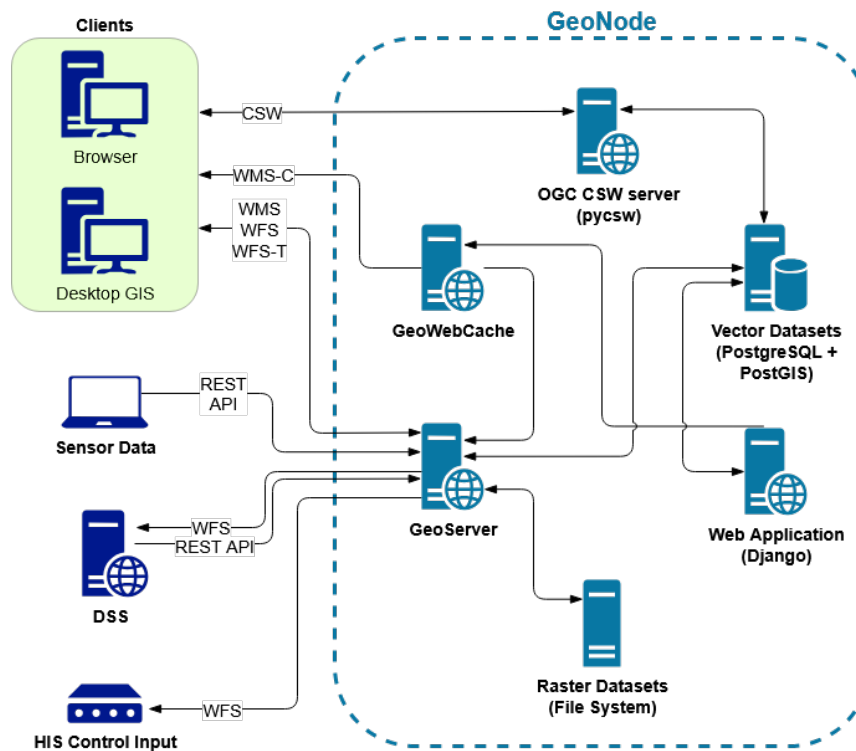


FIGURE 5.2: The individual components of GeoNode and how they are connected to the rest of the ICT components in the ADDFerti project (modified from Corti et al. (2018)).

could be supplemented with metadata, facilitating searchability and standard-compliant cataloging. Depending on the data type, uploaded datasets were automatically ingested into either the PostGIS database or the file-based storage system and subsequently published as OGC-compliant services via GeoServer.

The platform supported user interaction: styling of layers using the styled layer descriptor standard, direct editing of vector attributes and geometries through the web interface, and the creation of thematic maps and dashboards (see Figure 5.4). GeoNode supported on-the-fly re-projection to Web Mercator, allowing overlay with base maps such as OpenStreetMap or Google Satellite. Access control could be defined granularly at the layer and map level, including permissions for viewing, downloading, metadata editing, and data modification.

All published datasets were accessible through a suite of standardized interfaces including WMS, WFS(-T), WCS, and CSW, as well as RESTful APIs, which enabled seamless integration with the DSS, sensor data ingestion pipelines, and third-party GIS software such as QGIS and ArcGIS.

A short overview off the role of GeoNode in the project ADDFerti was also published in Steiger (2024)⁸.

⁸Available at: https://geomv.de/wp-content/uploads/2024/09/Tagungsband_GeoForum-MV-2024_epdf.pdf#page=197

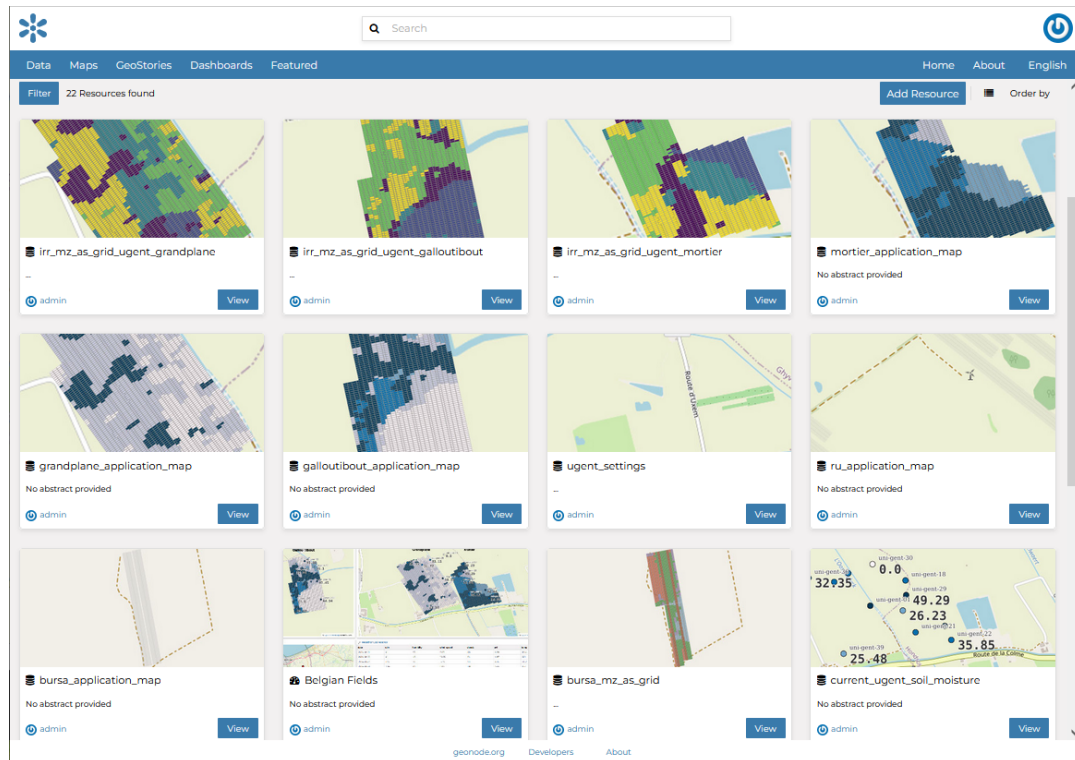


FIGURE 5.3: Screenshot of the user interface of GeoNode.

5.2 Data Pipelines: Data Collection, Processing and Integration

This section provides an overview of the data pipelines and interface workflows that facilitate the automated collection, transformation, and integration of spatial data into the ADDFerti SDI. Besides the automated data pipelines, data was also uploaded manually to the geoportal, which included the lab data of each field, the outlines of the fields and the pre-drawn grid cells for each field.

5.2.1 Interface: Soil Moisture Data to SDI

The technical procedure for downloading soil moisture data from LoRaWAN sensors into the local database was described in Section 4.1.3. The next step was to integrate the sensor data into the SDI.

For this, a Python script⁹ was developed to query the internal PostgreSQL database for the most recent reading of each soil moisture sensor. Using the GeoPandas library¹⁰, these readings are transformed into a geospatial point vector layer. The resulting dataset is then uploaded to GeoNode via its REST API as a new or updated vector layer. This enables dynamic visualization of current soil moisture conditions within the WebGIS interface and downstream use in the DSS.

⁹<https://github.com/AlexSteiger/fertigationMap/blob/master/currentSMC>

¹⁰<https://geopandas.org>

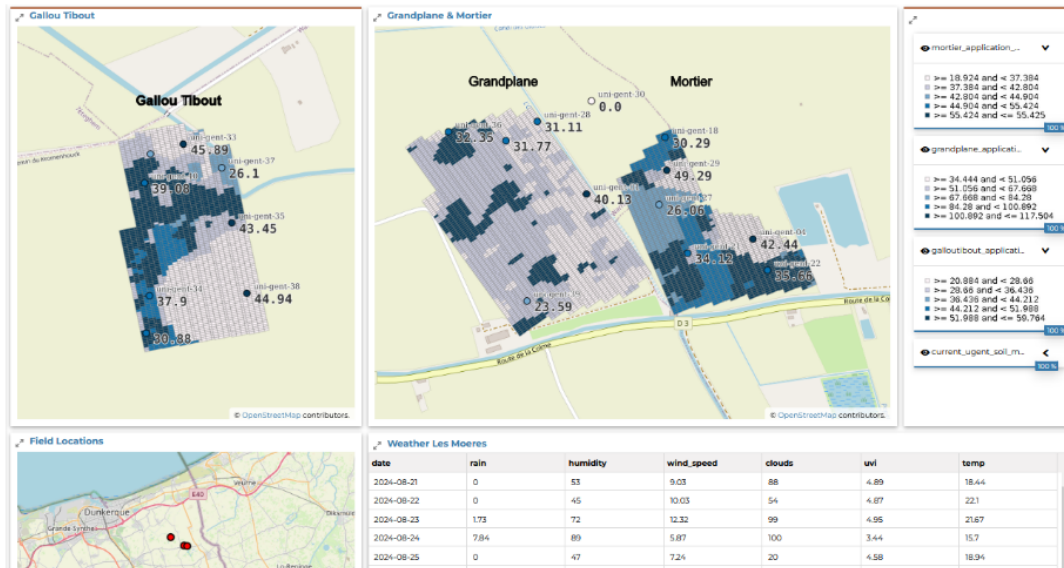


FIGURE 5.4: Screenshot of a dashboard created in GeoNode, showing the current application maps and soil moisture contents of the test sites in Belgium in 2024.

5.2.2 Interface: Weather Data to SDI

For weather data the service OpenWeather¹¹ was used, which provided a global 7-day forecast through its public API. OpenWeather aggregates its data from a combination of global meteorological agencies, airports, buoys, private sensor networks, radar stations, and weather satellites (OpenWeather, 2025). The available parameters include daily forecasts for precipitation, temperature, humidity, dew point, wind speed, cloud cover, and UV index.

For the implementation, a Python script¹² was deployed on the ADDFerti server to automate the retrieval and integration of weather forecasts for the locations of the experimental sites in France, Germany, and Turkey. The script makes scheduled API calls to OpenWeather, retrieves the relevant forecast data, and – similar to the soil moisture pipeline – transforms the results into a geospatial point vector layer using the GeoPandas library before uploading it to GeoNode via its REST API, either as a newly created layer or as an update to an existing one.

Representing weather forecasts as geospatial datasets enables the application of geoprocessing algorithms in later stages. For example for measuring the distances between forecast datasets and study sites or comparing the point-based forecast to raster-based weather radars.

5.2.3 Interface: SDI to DSS

The DSS in ADDFerti regularly generated VRFI application maps based on the most up-to-date data available within the SDI. As the DSS does not maintain

¹¹<https://openweather.org/>

¹²<https://github.com/AlexSteiger/fertigationMap/tree/master/rainForecastAdapter>

its own local data storage, all required inputs were retrieved dynamically from the geoportal, and outputs were uploaded back to it. For data retrieval, the DSS used the WFS interface of the geoportal to download geospatial datasets. For data publication, it employed the REST API to update newly generated application maps.

The data retrieved from the geoportal included:

- Soil moisture sensor data
- Weather forecast data
- Field geometries (grid cells)
- Laboratory data (field capacity, permanent wilting point)
- Management zones

The data uploaded from the DSS to the geoportal consisted of:

- Application maps for VRFI

This bidirectional exchange ensured that the DSS always operated on current datasets and that its recommendations were immediately accessible through the WebGIS interface and OGC services.

5.2.4 Interface: SDI to HIS

In ADDFerti, fertigation application maps were transferred from the GeoNode-based SDI to the HIS for execution in the field. The HIS GUI, installed on an industrial touchscreen panel, provides a dedicated function for querying, selecting, and downloading maps directly from the geoportal.

To support this, the HIS initiates a `GetCapabilities` request to the geoportal's WMS, which returns a list of available map layers. This list is filtered for layers containing the keyword `application_map` and displayed to the operator as a selectable list (see Figure 5.5; Listing 5.1). Upon selection, the corresponding map is retrieved via a Web WFS `GetFeature` request and ingested in GeoJSON format for further processing by the HIS software (see Listing 5.2).

In scenarios where internet connectivity is unavailable, maps can alternatively be transferred offline via USB in ESRI Shapefile format. The HIS also provides the ability to manually adjust fertigation rates per cell or even create application maps directly on the GUI when no preconfigured map is available.

```
import requests
import xml.etree.ElementTree as ET

url = 'https://geoportal.addferti.eu/geoserver/ows?service=WMS&
      version=1.1.1&request=GetCapabilities'
response = requests.get(url)

# Parse the XML content
root = ET.fromstring(response.content)
```

```
# Find all Layer names using the Name element
layer_names = [layer.find('Name').text for layer in root.findall("./Layer")]

# Filter list for application maps
layer_names = [name for name in layer_names if 'application_map' in name]

print("List of Application Maps:")
print(layer_names)
```

LISTING 5.1: Python script for retrieving the names of the available application maps from the geoportal using a WMS GetCapabilities request.

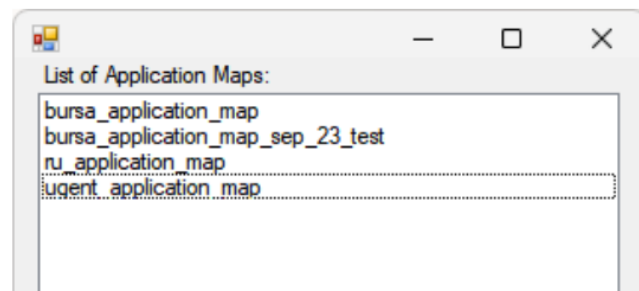


FIGURE 5.5: User interface of the HIS showing a list of available fertigation application maps. The layer names are retrieved from the geoportal via a WMS GetCapabilities request and displayed for operator selection.

```
# Application map for the test field in Germany:
curl -k "https://geoportal.addferti.eu/geoserver/ows?service=WFS&
version=1.0.0&request=GetFeature&typename=geonode%3
Aru_application_map&outputFormat=JSON&srs=EPSG%3A4326&
format_options=charset%3AUTF-8" --output ru_application_map.json

# Application map for the test field in Turkey:
curl -k "https://geoportal.addferti.eu/geoserver/ows?service=WFS&
version=1.0.0&request=GetFeature&typename=geonode%3
Abursa_application_map&outputFormat=JSON&srs=EPSG%3A4326&
format_options=charset%3AUTF-8" --output bursa_application_map.
json

# Application map for the test field in Belgium:
curl -k "https://geoportal.addferti.eu/geoserver/ows?service=WFS&
version=1.0.0&request=GetFeature&typename=geonode%3
Augent_application_map&outputFormat=JSON&srs=EPSG%3A4326&
format_options=charset%3AUTF-8" --output ugent_application_map.
json
```

LISTING 5.2: Example requests for downloading specific application maps from the geoportal via WFS GetFeature requests.

The WFS requests are structured the following:

- **service=WFS**: Specifies that the request is for a Web Feature Service (WFS).
- **version=1.0.0**: The version of the WFS service.
- **request=GetFeature**: Requests the actual feature data.
- **typename=geonode%3Aru_application_map**: Specifies the dataset (encoded as geonode:ru_application_map).
- **outputFormat=JSON**: Ensures output is in JSON format.
- **srs=EPSG%3A4326**: Requests the data in WGS 84 coordinate system.
- **format_options=charset%3AUTF-8**: Ensures correct character encoding.
- **-output ru_application_map.json**: Saves the output locally on the server.

Chapter 6

The ADDFerti Automatic Decision Support System for Fertigation

In ADDFerti, VRFI recommendations were provided as a single spatial dataset by combining irrigation and fertilization application maps. Fertilization maps were derived from fertilization MZs, which were established at the beginning of the season. Irrigation maps were also based on irrigation MZs, but additionally integrated current soil moisture measurements from in-field sensors, soil hydraulic properties such as field capacity and permanent wilting point, and weather forecasts. This section uses the Kassow experimental field in Germany as an example. For each field, the DSS allowed the configuration of custom settings, such as root depth or user-defined fertilizer quotas.

The conceptual and theoretical framework of the DSS was developed collaboratively by UGent, BUŮ, and RU. The technical implementation was carried out by RU.

The automatic DSS was implemented as a set of Python scripts deployed on the project server, executed every ten minutes to update fertigation application maps in near real time. The source code is available at <https://github.com/AlexSteiger/fertigationMap>. Most datasets were automatically retrieved from the ADDFerti geoportal, while certain static datasets (e.g., laboratory-derived soil hydraulic properties) were uploaded manually at the start of the season. The following subsections describe the step-by-step creation of fertigation application maps in detail.

6.1 Management Zone Delineation

MZs represent areas of homogeneous characteristics relevant for irrigation and fertilization management. In the ADDFerti project, they were delineated using k-means cluster analysis based on multiple soil and crop parameters. Irrigation MZs formed the basis for irrigation application maps, while fertilization rates were derived directly from fertility MZs.

The input dataset for irrigation MZs included soil moisture content, TOC, clay content, and NDVI, the latter calculated as the mean of all cloud-free Sentinel-2 images from the previous growing season. For the Kassow site in Germany, the topographic wetness index (TWI), derived from a 1 m digital elevation model (DEM), was also included to account for terrain-driven water

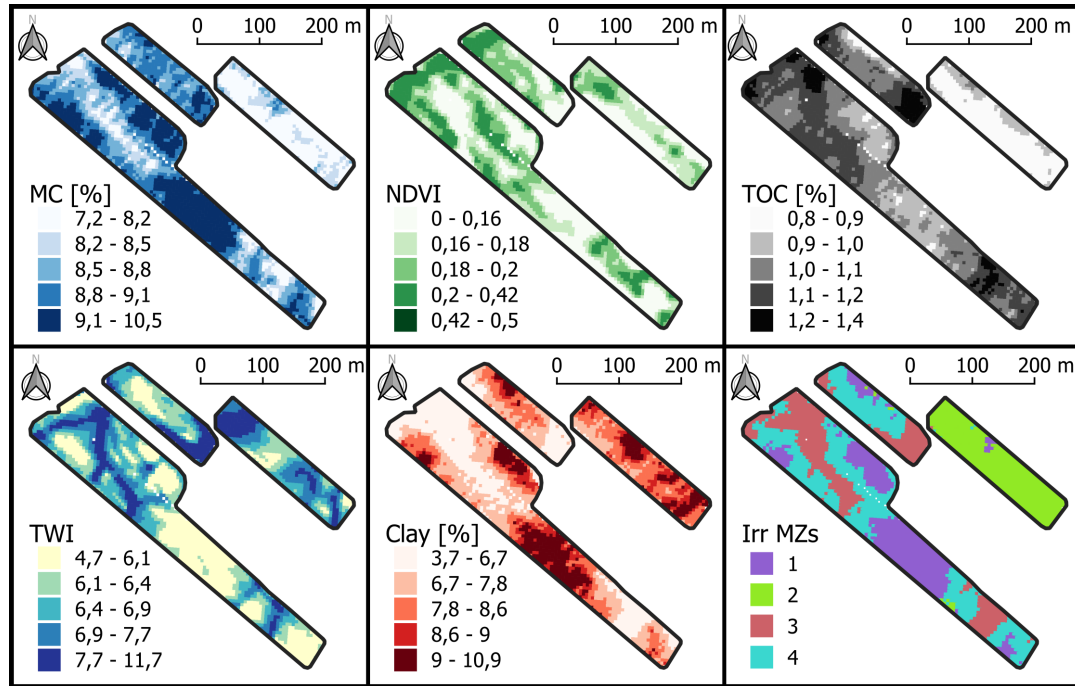


FIGURE 6.1: The used properties to calculate the irrigation MZs for the north-east area of the field in Kassow, Germany, shown as an example.

distribution; this parameter was omitted for the other, predominantly flat, sites.

For soil fertility MZs, the input datasets comprised (1) chemical and physical soil properties measured by the vis-NIR multi-sensor platform of UGent, typically including P, K, Mg, Ca, CEC, pH, MC, and clay content; (2) NDVI; and (3) previous years' yield data, if available.

6.2 Pre-processing

Pre-processing involves two main tasks: (1) adjusting the geometry of the application maps to match the topography of the field, and (2) preparing the static field data.

The final pre-processing step ensures that the DSS can operate efficiently by consolidating all static information into a single spatial dataset. This is accomplished by spatially joining the MZs, laboratory-derived soil hydraulic properties, and soil moisture sensor locations with a predefined grid. As a result, all relevant attributes are stored in one unified layer, eliminating the need for repeated spatial joins during each update cycle. The procedure is carried out in a GIS environment and is performed once at the beginning of each season.

Grid and Tramlines

Fertigation is typically performed in multiple passes. After each pass, the HIS is moved orthogonally to the next tramline with a tractor. To prevent crop damage, the HIS generally operates on pre-existing tramlines within the field. With a working width of 46 m, the optimal tramline spacing is either 46 m or 23 m when using every second tramline. If the actual tramline spacing differs from these values, a decision must be made between leaving non-irrigated gaps or accepting overlaps. In the case of overlaps, the outer valves of the HIS can be shut off manually; however, this reduces the effective working width and lowers operational efficiency. Some farmers maintain fixed tramlines, while others change them between seasons. In either case, tramline positions have to be mapped in advance, either via GNSS survey or drone imagery. The choice of tramlines to be used, as well as the fertigation travel direction (determined by the location of the water supply), must be planned beforehand, since the application maps are generated accordingly.

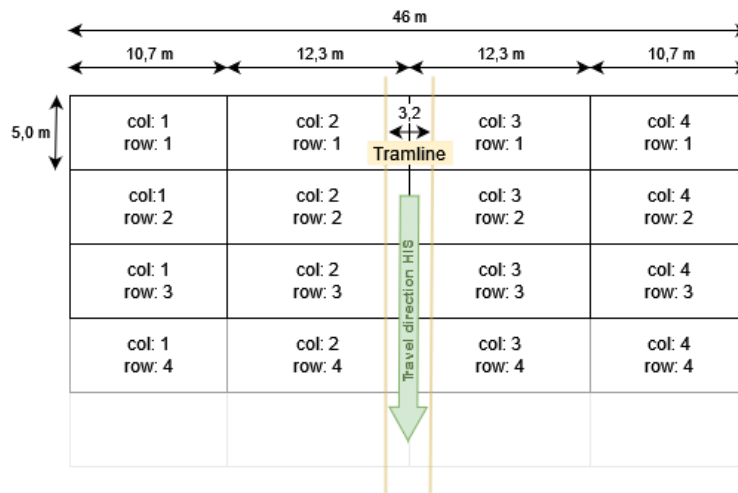


FIGURE 6.2: Grid cell dimensions and numbering layout for rows and columns, aligned with the HIS travel direction.

The application maps follow a cell-based layout. Each fertigation strip is divided into a grid aligned with the four control sections of the HIS. The grid cell length is 5 m. Cell widths are 10.7 m for the two outer sections and 12.3 m for the two inner sections, the latter including part of the 3.2 m-wide tramline (see Figure 6.2). For internal HIS processing, each grid cell is assigned the attributes `row`, `column`, and `field_id`. The `field_id` uniquely identifies each fertigation strip. Row and column numbering restarts for each strip, with columns counted from left to right and rows starting on the side opposite the HIS reel position (see Figure 6.3).

Joining all Layers to the unified Grid

The five datasets – irrigation MZs, fertilization MZs, laboratory data, soil moisture sensor locations, and the grid – were combined into a single dataset with

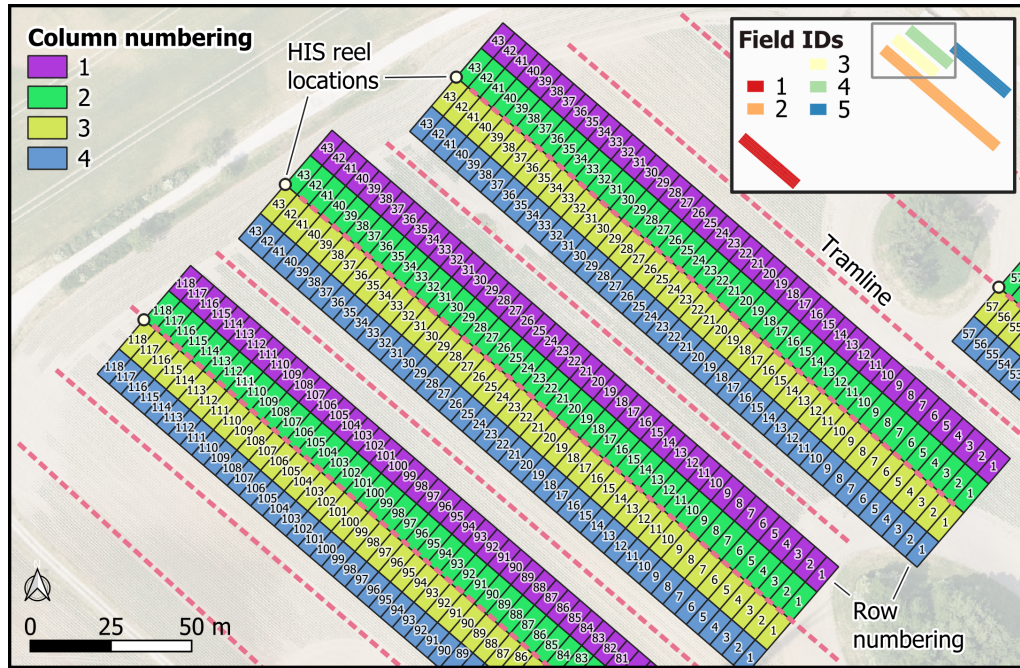


FIGURE 6.3: Placement of fertigation strips in relation to the tramlines.

a uniform spatial resolution using a QGIS model (see Figure 6.4). Employing a model-based workflow ensured not only significant time savings but also consistency in data units and attribute naming conventions across different test sites and seasons.

Irrigation and fertilization MZs were joined separately to the grid via spatial join. Each grid cell was assigned the MZ number with the largest spatial overlap, resulting in exactly two MZ attributes per cell (MZ_irr and MZ_fert).

The point-based laboratory dataset contains field capacity (FC), permanent wilting point (PWP), soil bulk density, and the location of each soil sample. Each MZ is required to contain at least one laboratory sample. The point-based sensor dataset contains sensor locations and the individual sensor IDs. These datasets were joined to the grid using a nearest-neighbour approach, with the additional condition that the laboratory and sensor point must lie respectively within the same irrigation MZ as the target grid cell. This ensures that the assignment of laboratory and sensor data is not based solely on proximity, but also respects the MZ boundaries (see Figure 6.5).

Irrigation MZs were chosen as the reference for this process because they were delineated using attributes directly related to the laboratory and sensor data (e.g., clay content, topography, and soil moisture content). This MZ-based approach avoids arbitrary interpolation and ensures that the static attributes within each grid cell are consistent with the zone-specific soil characteristics.

The result of this pre-processing was a harmonized, grid-based dataset containing all static attributes required for DSS operation. This dataset was uploaded to the Geoportal at the beginning of the season, where it served as

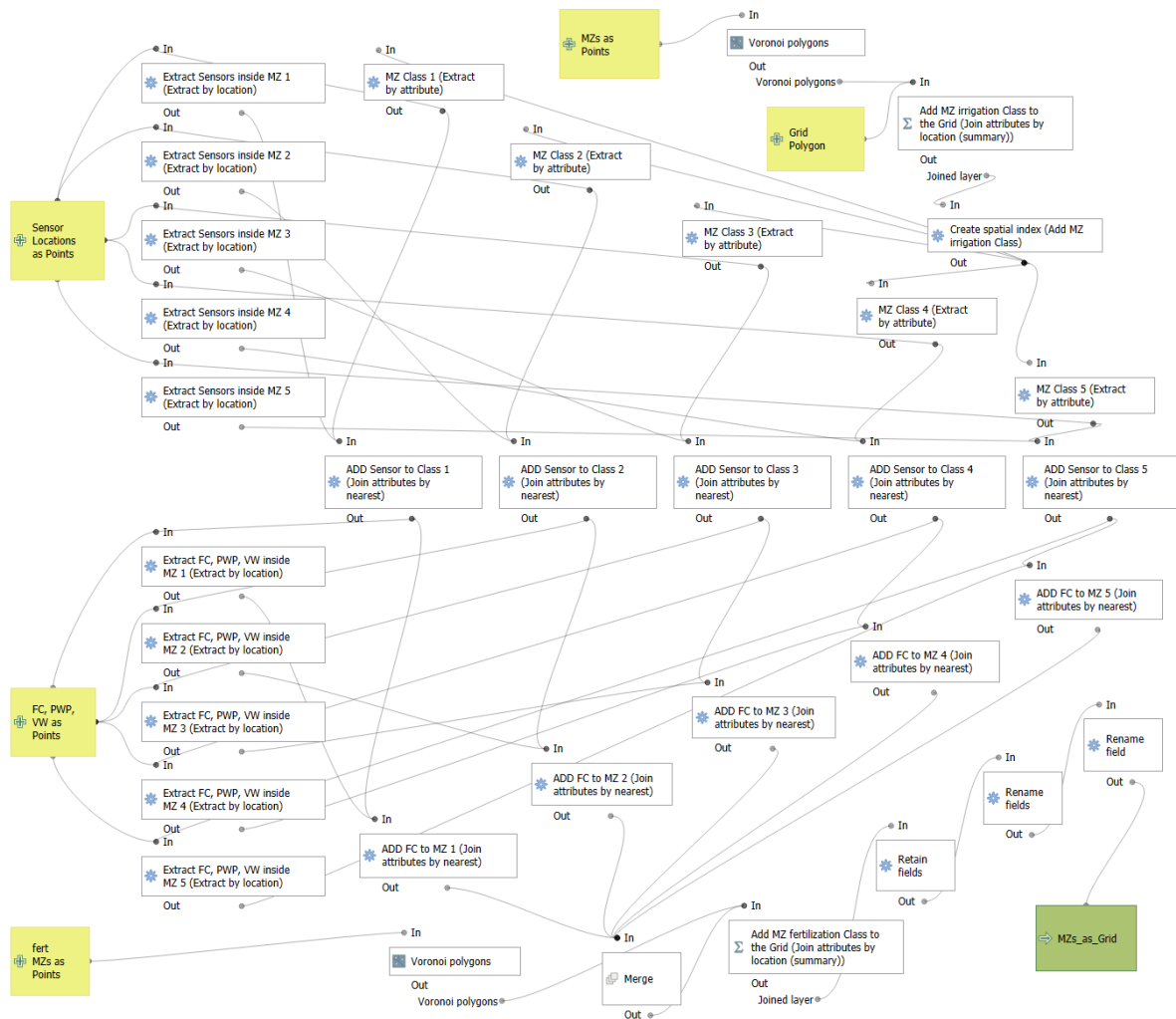


FIGURE 6.4: Screenshot of the QGIS-Model for joining the layers into one unified dataset. The model is accessible at: <https://github.com/AlexSteiger/fertigationMap/tree/master/PreProcessing>

the reference layer for automatic fertigation map generation. Figure 6.6 shows an example section of the unified dataset.

6.3 Creating Application Maps

This section presents the algorithms and formulas implemented in the automatic DSS for calculating irrigation and fertilization rates. The source code of the DSS is available at <https://github.com/AlexSteiger/fertigationMap/tree/master/fertigationMap>.

6.3.1 Irrigation Application Rates

Irrigation application maps specify the planned site-specific water volumes for the upcoming irrigation event. Recommendations are based on real-time soil moisture sensor data, soil hydraulic properties (field capacity and permanent

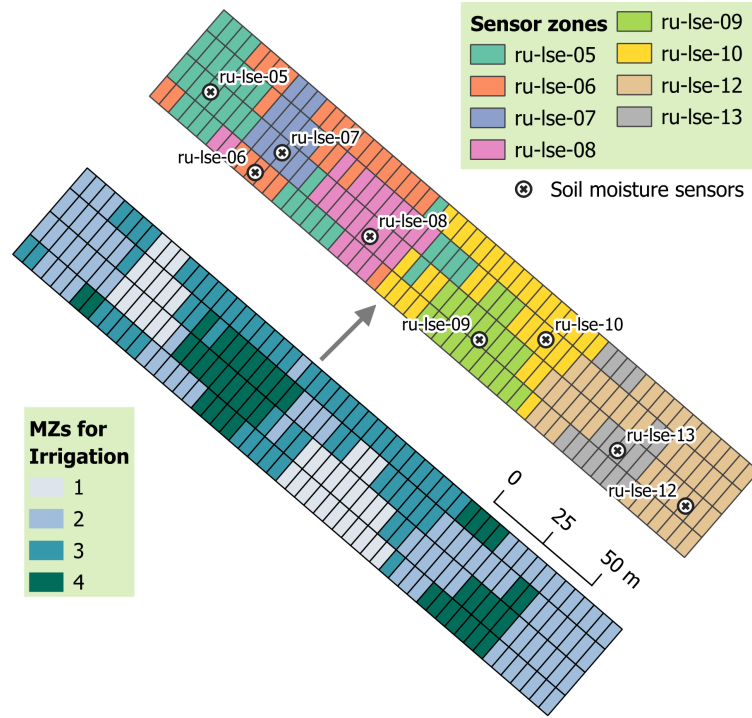


FIGURE 6.5: Translation of the irrigation MZs into corresponding sensor zones of one fertigation strip of the Kassow test field.

wilting point), weather forecasts, MZs, and user-defined global settings. The irrigation requirement for each grid cell is calculated using a water balance model suggested by BUÜ.

During rainfall or irrigation, soil pores may become saturated, meaning all pores are filled with water and no air remains. After gravitational drainage, the soil reaches field capacity (FC), when large pores contain air while smaller pores remain water-filled. At FC, the balance of water and air in the soil is generally considered optimal for crop growth. As plants extract water, the soil dries until water is held too tightly for roots to absorb. This corresponding water content is the permanent wilting point (PWP), conventionally defined at a soil matric potential of -1.5 MPa (-15 bar) (Kirkham, 2005). The water available to plants is therefore the difference between FC and PWP, called available water (AW). To avoid plant stress, irrigation is usually scheduled before depletion reaches PWP, at a threshold defined as the management allowable depletion (MAD), typically set to 50–60% of AW (see Figure 6.7) (Brouwer et al., 1985).

Soil water content can be expressed on a gravimetric or volumetric basis. Gravimetric water content (θ_g) is the mass of water per mass of dry soil. It is measured in the lab by weighing a fresh soil sample (m_{wet}), drying it to remove all water, and weighing the dried soil (m_{dry}). It is calculated as:

$$\theta_g = \frac{m_{wet} - m_{dry}}{m_{dry}}. \quad (6.1)$$

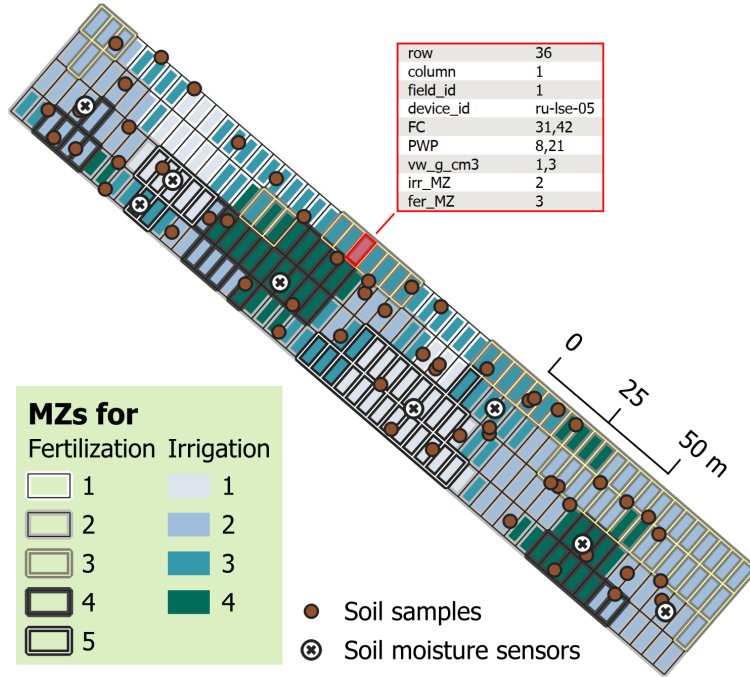


FIGURE 6.6: Unified dataset having MZs for irrigation and fertilization, soil samples for FC, PWP and bulk density, and soil moisture locations in the gridded format.

Volumetric water content (θ_v) is the volume of liquid water per volume of soil:

$$\theta_v = \frac{V_{water}}{V_{soil}}. \quad (6.2)$$

It can be converted from gravimetric content using

$$\theta_v = \frac{\theta_g \cdot \rho_b}{\rho_w}, \quad (6.3)$$

where ρ_b is the soil bulk density [g/cm^3] and $\rho_w \approx 1$ [g/cm^3] is the density of water.

For irrigation, volumetric water contents are commonly expressed as an equivalent water depth (mm) over a given root depth:

$$\theta_{mm} = \theta_v \cdot \text{depth}. \quad (6.4)$$

Within the DSS, the gravimetrically measured FC and PWP are first converted into volumetric water contents for a given soil depth (e.g. 300 mm) using equations (6.3) and (6.4), resulting in:

$$\theta_{mm,FC} = \theta_{g,FC} \cdot \rho_b \cdot \text{depth}, \quad (6.5)$$

$$\theta_{mm,PWP} = \theta_{g,PWP} \cdot \rho_b \cdot \text{depth}. \quad (6.6)$$

The root depth corresponds to the irrigation depth, which ideally equals the

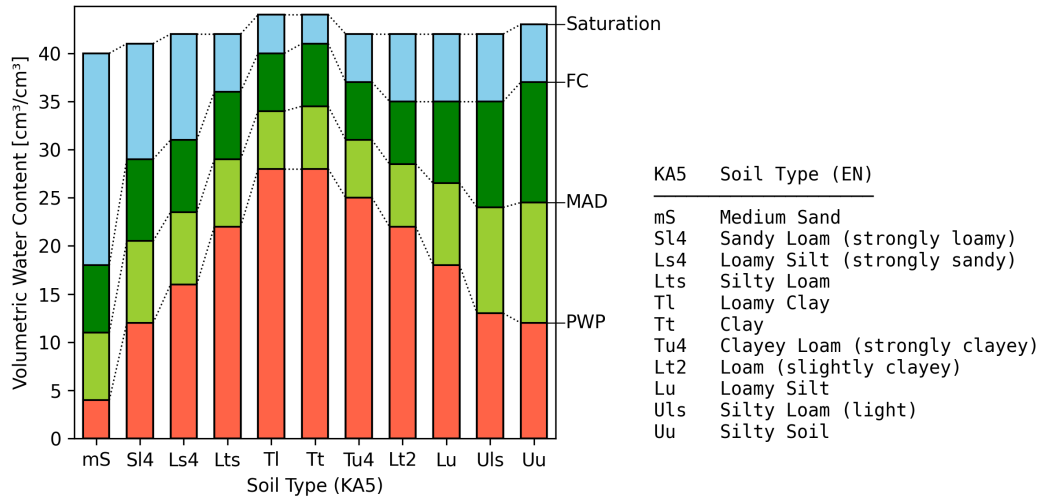


FIGURE 6.7: FC, PWP, and MAD values for 11 selected soil types. Soil water retention characteristics are based on the reference values provided in the 'Bodenkundliche Kartieranleitung' (KA5), Table 75 (Sponagel, 2005).

current rooting depth of the crop. Soil moisture sensors directly provide volumetric values ($\theta_{v,MC}$), which can also be expressed as water depth:

$$\theta_{mm,MC} = \theta_{v,MC} \cdot \text{depth}. \quad (6.7)$$

Available water is then defined as

$$\theta_{mm,AW} = \theta_{mm,FC} - \theta_{mm,PWP}, \quad (6.8)$$

and the management allowable depletion as

$$\theta_{mm,MAD} = \theta_{mm,PWP} + \theta_{mm,AW} \cdot MAD_{\text{set}}, \quad (6.9)$$

with MAD_{set} typically 0.5 (50%).

Finally, the irrigation need (IN) for each grid cell is calculated as

$$\theta_{mm,IN} = \theta_{mm,FC} \cdot \text{fill_up_rate} - \theta_{mm,MC} - \theta_{mm,Rain}, \quad (6.10)$$

where the fill-up rate (default 0.9) limits refilling to 90% of FC to avoid oversaturation, while the parameter $\theta_{mm,Rain}$ represents the expected precipitation in the 7-day forecast in mm.

For practical use, IN can be converted from mm to liters per hectare:

$$IN [l/ha] = \theta_{mm,IN} \cdot 10,000, \quad (6.11)$$

since 1 mm corresponds to 1 L/m², or 10,000 L per hectare.

Variable definitions:

- $\theta_{g,FC}, \theta_{g,PWP}$: gravimetric water contents at FC and PWP [g/g]
- ρ_b : soil bulk density [g/cm³]
- $\theta_{v,MC}$: volumetric soil moisture content [cm³/cm³]
- $\theta_{mm,X}$: water column over profile depth for parameter X [mm]
- $\theta_{mm,X}$: equivalent water depth of X (FC, PWP, MC, AW, MAD, IN, Rain) [mm]
- MAD_{set} : management allowable depletion setting (default 0.5 = 50%)
- depth: set irrigation / root depth [mm]
- fill_up_rate: fraction of FC used for refill (default 0.9 = 90%)

In practice, the DSS requires three input datasets to calculate irrigation rates: (1) static data from the unified dataset produced during pre-processing, (2) live soil moisture sensor data, and (3) weather forecast data.

All datasets are retrieved from the Geoportal via WFS. Within the DSS, they are checked for a consistent coordinate reference system, reprojected if necessary, and merged into a single pandas GeoDataFrame. Subsequently, equations (6.5) to (6.11) are executed for each grid cell. Several parameters can be configured by the user, including the fill-up rate (Eq. 6.10), the effective root depth (Eqs. 6.5, 6.6, 6.7), and the MAD_{set} (Eq. 6.9). In addition, minimum and maximum irrigation limits can be specified; in particular, defining a maximum threshold helps avoid excessive applications in case of input errors or unusual field conditions.

The resulting maps provide site-specific irrigation recommendations that combine soil hydraulic properties, real-time sensor and weather data, and user-defined settings. An example output of the irrigation DSS is shown in Figure 6.8.

The workflow for generating irrigation prescriptions is also presented in Steiger et al. (2023), which describes the process from input data to final application maps in a condensed form for the Kassow site, using TWI, NDVI, FC, PWP, and the rainfall forecast as input parameters.

6.3.2 Fertilizer Application Rates

Fertilizer recommendation maps are derived directly from the fertility MZs, which are included in the unified dataset produced during pre-processing. To facilitate subsequent calculations, when producing the MZs, they are also directly numbered in order of fertility, with MZ 1 representing the least fertile area and the highest-numbered MZ representing the most fertile area.

The DSS uses these ordered and gridded fertility MZs to calculate fertilizer recommendations for the next application. The recommended fertilizer amount, expressed in litres per hectare, is computed for each MZ as the product of a user-defined base rate and a zone-specific quota:

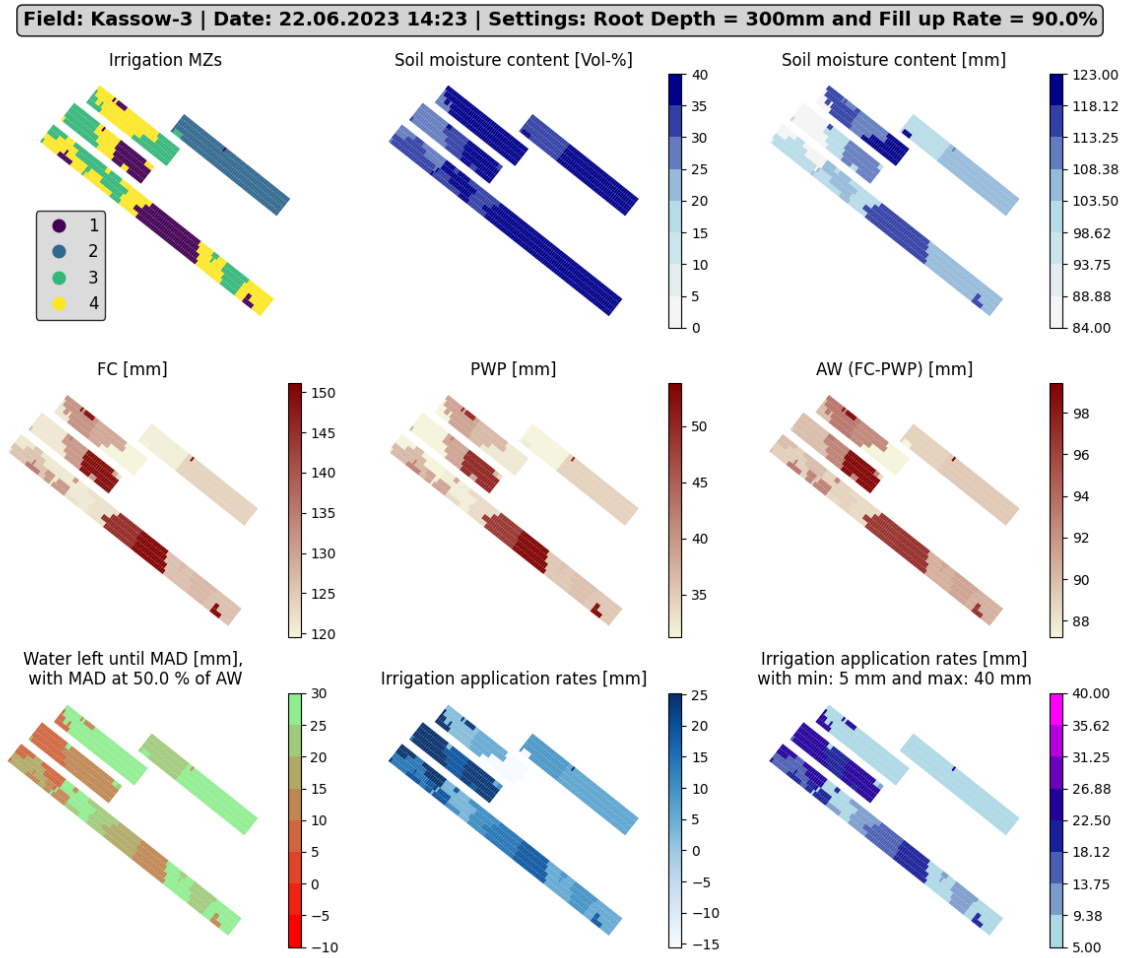


FIGURE 6.8: Example output of the irrigation DSS for part of the field in Kassow, Germany. The plots are automatically generated while executing the DSS.

$$\text{fer_l_ha} [l/ha] = \text{fer_user_rate} [l/ha] \cdot \text{fer_quota} [\%]. \quad (6.12)$$

The parameter `fer_user_rate` represents the user-defined base application rate, while `fer_quota` specifies the relative adjustment for each MZ. These quotas can be flexibly adjusted within the DSS.

By default, the system applies the *Robin Hood scheme* as outlined by Guerrero and Mouazen (2021), in which less fertile zones receive proportionally more fertilizer and highly fertile zones proportionally less. For example, if five MZs are defined, the base application rate is applied to the intermediate zone (MZ 3). MZ 1 and MZ 2 then receive +50% and +20% relative to the base rate, while MZ 4 and MZ 5 receive -25% and -50%, respectively. This approach ensures that nutrient supply compensates for underlying fertility differences across the field.

This scheme involves applying more fertilizer to the least fertile zones (e.g., L and ML) and less fertilizer to the most fertile zones (e.g., H and MH), according

to the principles outlined by Guerrero and Mouazen (2021).

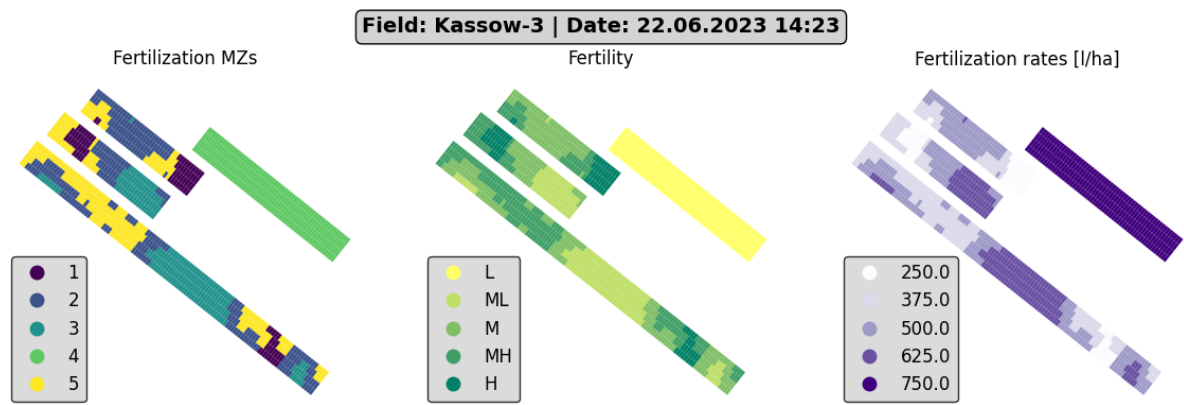


FIGURE 6.9: Example output of the fertilization DSS for part of the field in Kassow, Germany.

6.3.3 Fertigation Application Maps

The final step in the DSS workflow is the creation of fertigation application maps, by writing all necessary informations (irrigation rates, fertilization rates, grid cell identifiers and geometries) into a single spatial dataset and finally uploading them to the Geoportal (see Figure 6.10).

Combining both layers into one fertigation map simplifies machine operation by ensuring that only a single map needs to be transferred to the HIS, thereby reducing handling effort and minimizing the risk of inconsistencies or upload errors.

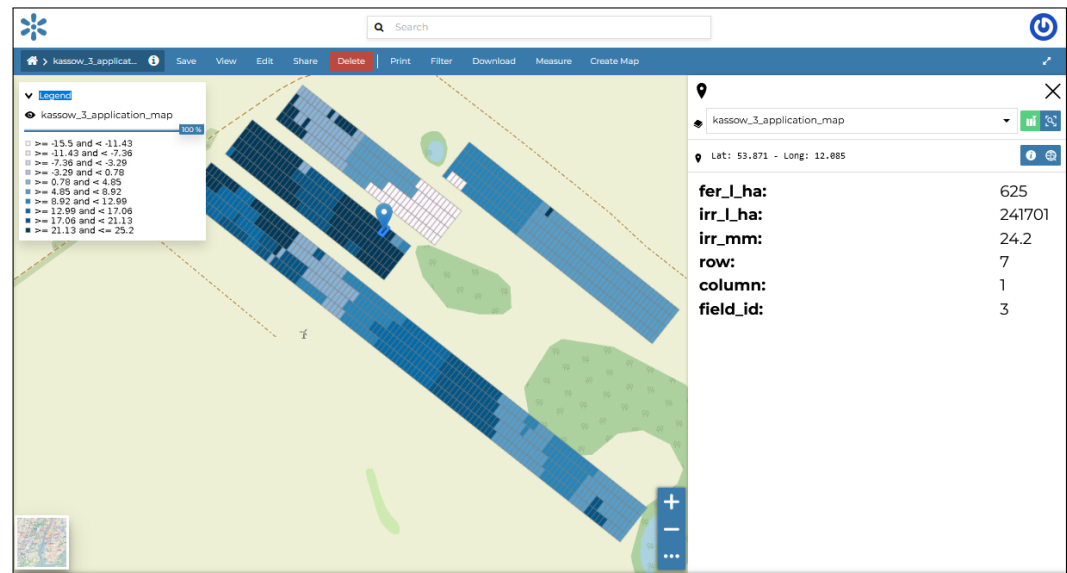


FIGURE 6.10: Fertigation application map for Field 3 in Turkey displayed in the geoportal, illustrating spatially variable irrigation and fertilization rates. Fertilizer application is stored in the `fer_l_ha` attribute (L ha^{-1}), while irrigation is provided as `irr_l_ha` (L ha^{-1}) and `irr_mm` (mm).

Chapter 7

Validation of the Whole System: Case Study in Turkey

This chapter describes the field experiments done 2023 for Field 3 in Turkey (see Figure 3.4 in Section 3.2.3), which culminated in a trial run of the HIS in August 2023.

Soil mapping and delineation of MZs were carried out by UGent; laboratory analyses of MC, FC, and PWP as well as the HIS field experiments were conducted by BUÜ; NDVI calculations were performed by RU; the HIS was modified by Sezer and BUÜ; and the ICT infrastructure for data management and application map generation was developed and maintained by RU.

7.1 Results from the vis-NIR Multi-Sensor Soil Scanning Platform

Soil scanning was carried out in Field 3 by transporting the UGent on-line multi-sensor platform to Turkey. The on-line visible and near-infrared (vis-NIR) multi-sensor platform developed by Mouazen and Ramon (2006) was used to collect soil spectra on July 14, 2023.

Parallel to the on-line measurements, 24 random soil samples were collected from Field 3 at a depth of approximately 15 cm. Each sample was reduced to a sub-sample of 100 g to 150 g, which was used for laboratory vis-NIR scanning. The samples collected during the on-line scanning were also analyzed for soil moisture content using the oven-dry method at 105 °C for 24 h, as well as for field capacity (FC) and permanent wilting point (PWP). FC was determined at 2.54 pF (1/3 atm) and PWP at 4.2 pF (15 atm) using a pressure membrane apparatus with undisturbed soil samples. Due to budget constraints, no laboratory analyses could be conducted for P, K, Mg, Ca, CEC, pH, or clay.

7.1.1 Calibration Models for Soil Properties in Field 3

Calibration models for Field 3 were developed using partial least squares (PLS) regression for P, K, Mg, Ca, CEC, pH, MC, and clay. Since only MC could be analyzed directly, existing laboratory data from 110 soil samples collected in the nearby Field 1 and Field 2 in 2021 were used to construct the calibration

TABLE 7.1: PLSR model results for predicting soil properties in Field 3. Models for P, K, Mg, Ca, CEC, pH, and clay are based on lab analyzed data from Field 1 and Field 2, while the MC model includes data from Field 1, Field 2, and Field 3.

	Training set			Validation set		
	R^2	RMSE	RPD	R^2	RMSE	RPD
P	0.99	0.44	16.30	0.66	4.05	1.74
K	0.79	5.32	2.19	0.75	5.63	2.04
Mg	0.67	3.45	1.76	0.66	3.76	1.73
Ca	0.85	3.23	2.55	0.73	3.12	1.96
CEC	0.87	2.55	2.78	0.76	2.85	2.07
pH	0.60	0.27	1.59	0.69	0.25	1.81
MC	0.94	0.81	4.14	0.78	2.37	2.17
Clay	0.66	3.03	1.72	0.52	3.57	1.47

Abbreviations: RMSE = root mean square error; RPD = residual prediction deviation.

models for the remaining properties. It was assumed that no major differences exist between these fields and Field 3.

The laboratory-analyzed soil samples and corresponding vis-NIR spectra were combined into a single dataset, which was randomly split into a calibration set (70%) and a validation set (30%). PLS regression with cross-validation was applied to the calibration set. Model performance was then evaluated using the validation set by comparing predicted with measured values. Accuracy was assessed using the coefficient of determination (R^2), root mean square error of prediction (RMSEP), and residual prediction deviation (RPD). The results are summarized in Table 7.1.

7.1.2 Soil and Crop Attribute Maps in Field 3

After the successful prediction of soil properties with the developed models, the prediction dataset, which included GNSS coordinates, was used to generate spatial maps of individual soil attributes. For each property, fitted semivariograms were constructed to describe the spatial variance of the data. These semivariograms served as the basis for interpolation using ordinary kriging (OK), resulting in high-resolution maps of soil properties for Field 3 (see Figure 7.1).

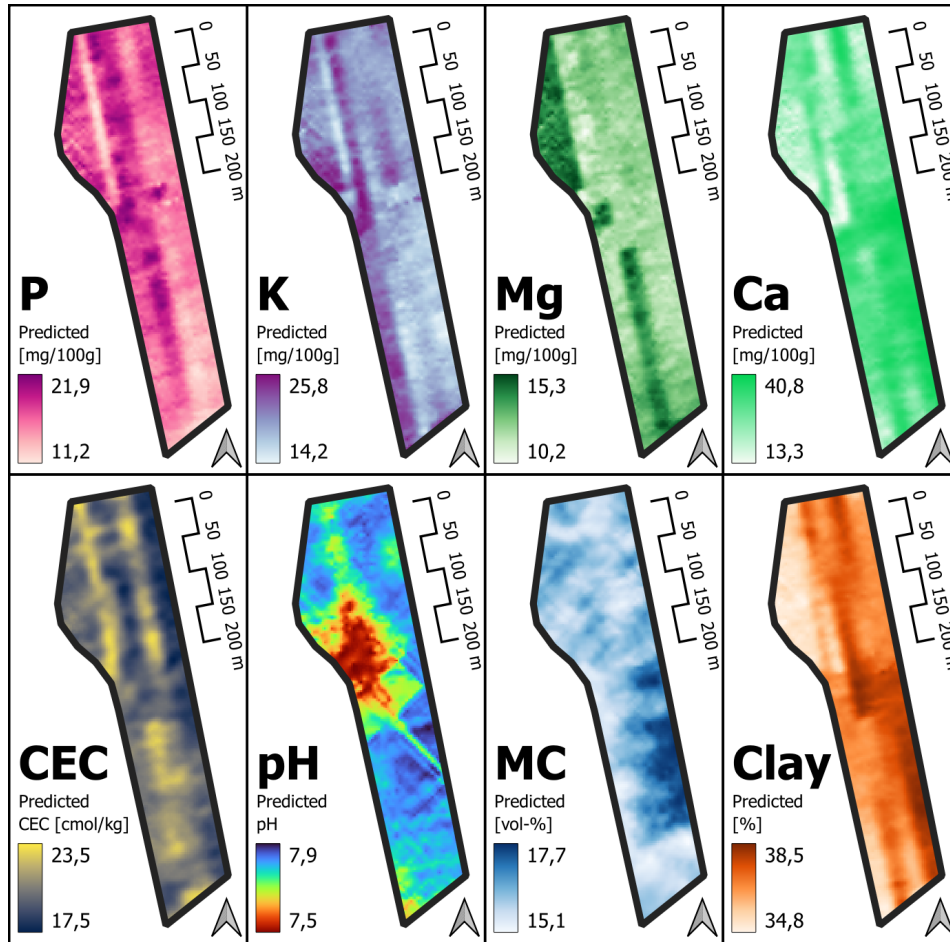


FIGURE 7.1: On-line vis-NIR predicted soil properties maps of Field 3 in Turkey in 2023.

7.2 Management Zone Delineation

MZs for irrigation in Field 3 in Turkey were delineated using MC and clay content predictions from the soil mapping, combined with the NDVI (see Figure 7.2). The NDVI was derived as the mean of all cloud-free Sentinel-2 images from the previous growing season using Google Earth Engine. Fertility MZs were generated from the vis-NIR multi-sensor predictions of soil chemical and physical properties together with the NDVI (see Figure 7.3).

For delineation, the input soil and crop properties were normalized and integrated using k-means clustering in R. Both irrigation and fertility MZs were classified into four classes, as this number provided the best balance between within-class homogeneity and between-class separation. Fertility classes were subsequently ranked and indexed from lowest to highest fertility.

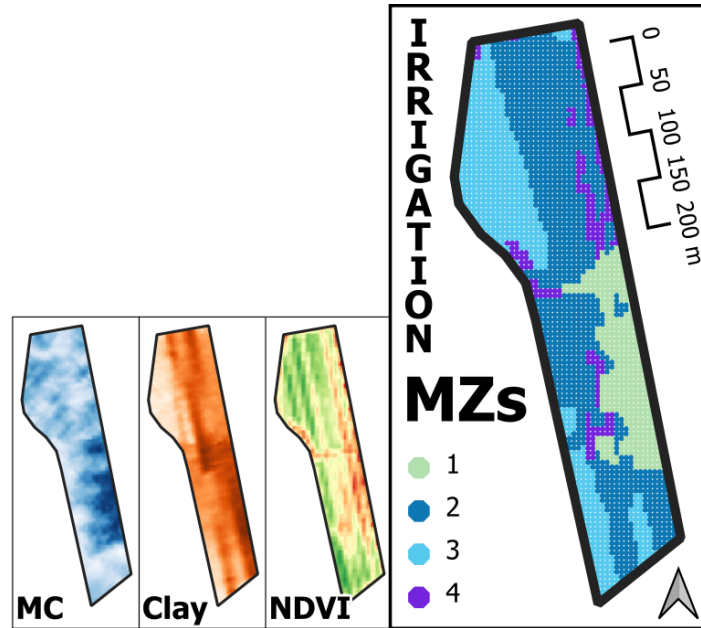


FIGURE 7.2: Input soil and crop properties used for delineating irrigation MZs for Field3 in Turkey.

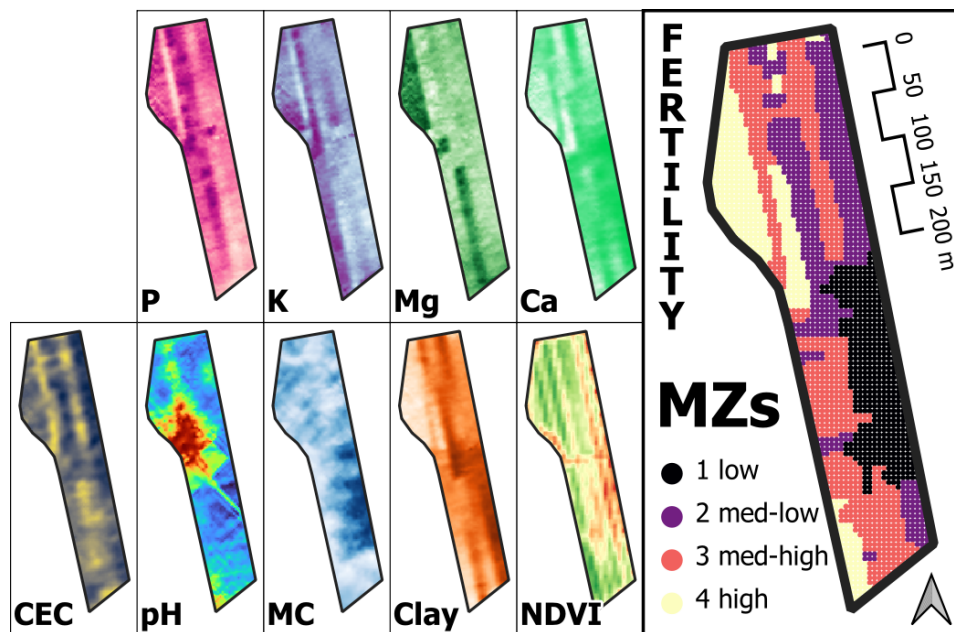


FIGURE 7.3: Input soil and crop properties used for delineating soil fertility MZs for Field3 in Turkey.

7.3 Performance of the LoRaWAN Soil Moisture Sensor Network

LoRaWAN Dragino LSE01 soil moisture sensors were installed on July 5 2023, at a depth of 30 cm. Sensor locations were selected in accordance with the delineated irrigation MZs. A Dragino DLOS8 LoRaWAN gateway was

deployed at a nearby farm, where access to the power grid and internet was directly available.

The sensors transmitted real-time soil moisture data to the ADDFerti cloud infrastructure via the pipeline described in Section 4.1.3. The data were stored in the project's SDI and visualized through a Grafana-based dashboard for live monitoring of soil moisture conditions (Figure 7.4). Data collection continued until shortly before harvest, when the sensors were removed on November 8 (Figure 7.5).

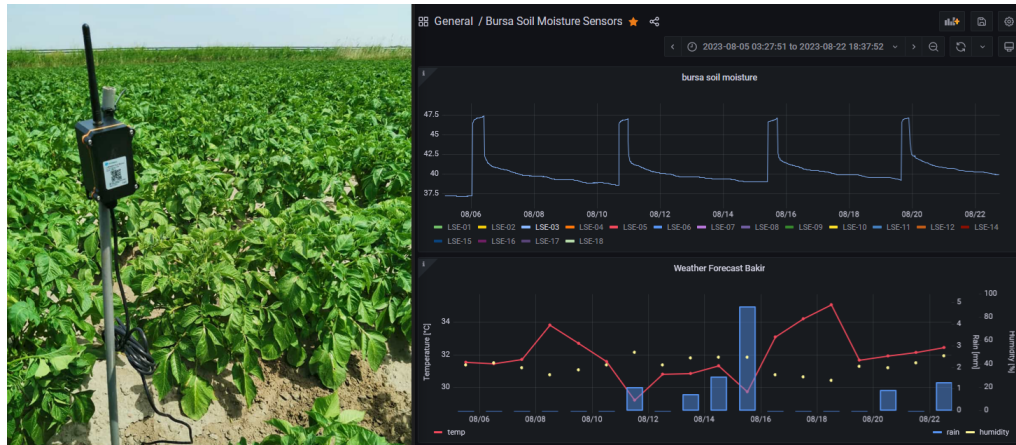


FIGURE 7.4: One soil moisture sensor installed in Field 3 (Turkey) and corresponding dashboard.

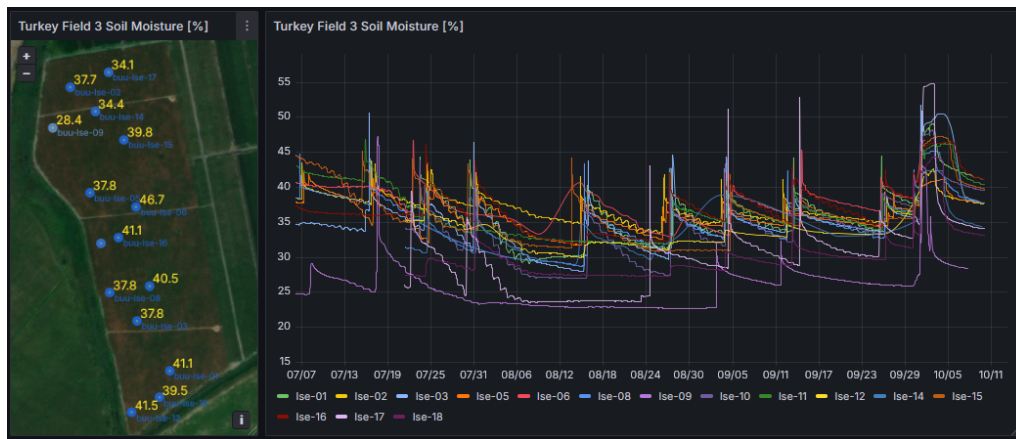


FIGURE 7.5: Dashboard with time-series data of all sensors installed in Field 3 (Turkey).

7.4 Generating Fertigation Maps, Fine-Tuning during Field Trial

Following the procedures described in Section 6, and after pre-processing, the DSS generated site-specific application maps for irrigation and fertilization for Field 3. These maps were based on the delineated MZs, the pre-planned

grid, interpolated FC and PWP maps, real-time soil moisture sensor data, and weather forecasts. The resulting maps were automatically uploaded to the geoportal.

The HIS field trial in Field 3 was conducted on 24 August 2023 by BUÜ, with RU. During the experiment, the DSS settings were fine-tuned to reflect local conditions. The effective root depth was set to 300 mm, and the fill-up rate to 90%. The farmer defined a target irrigation rate (user rate) of 30 mm, with a minimum of 10 mm. A maximum of 50 mm was specified to avoid excessively long irrigation events.

Figures 7.6 and 7.7 show the irrigation and fertilization maps, which were generated by the DSS and applied during the field experiment. Figure 7.8 shows the fertigation recommendation map as displayed in the geoportal. Application maps were downloaded directly in the field via the HIS GUI. The calculation of a fertigation map, including upload to the SDI, required about 30 s, after which it became immediately accessible to the HIS. This enabled on-site fine-tuning of the DSS settings without significant delays.

The field was fertigated in five strips of approximately 300 m length each. The fertigation of the 7 ha field was completed within two days, with each strip taking around 8 h. The 300 L fertilizer tank capacity was sufficient for one strip (about 8 h of operation). Figure 7.9 shows the HIS in operation on the day of the trial.

Tekin et al. (2025) introduces the developed VRFI system from a technical and mechanical standpoint and presents the results of measured vs. set water and fertilizer flow rates for the experiment conducted on Field 3. Overall, the field operation was completed without mechanical complications, and the developed control software functioned reliably. Upon downloading the application map, the system automatically calculated the required flow rates for each grid cell and optimized the valve openings, dosing pump speeds, and cart ground speed accordingly. During testing, the water flow sensors, proportional valves, and fertilizer dosing pumps operated without issues. The targeted irrigation rates were achieved with high accuracy ($R^2 = 0.96-0.99$), while the correspondence between set and applied fertilizer flow rates also proved reliable ($R^2 = 0.85-0.99$).

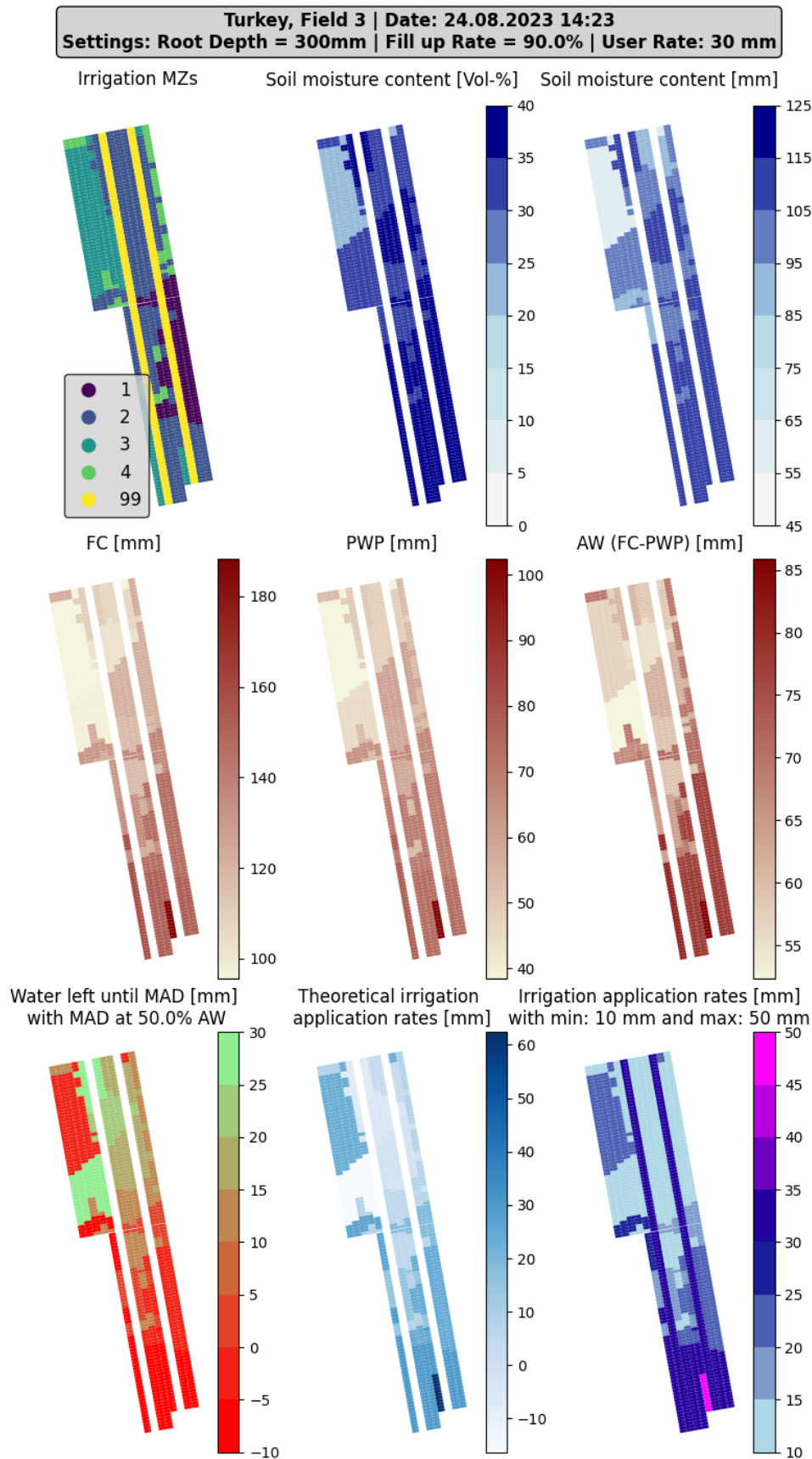


FIGURE 7.6: Irrigation application maps for Field 3 in Turkey generated by the DSS for 24 August 2023. The irrigation MZ classified as 99 (top left) represents the control zones with a constant user-defined rate of 30 mm. It can be observed (bottom left), that in some areas soil moisture content already is below the MAD.

The final irrigation rates are shown in the bottom right map.

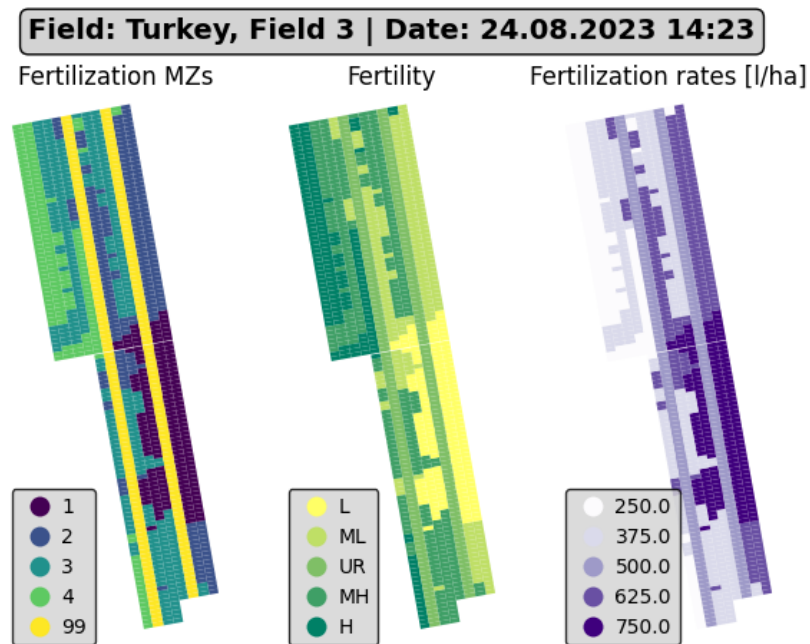


FIGURE 7.7: Fertilization application map for Field 3 in Turkey, generated by the DSS and applied during the field trial on 24.08.2023.

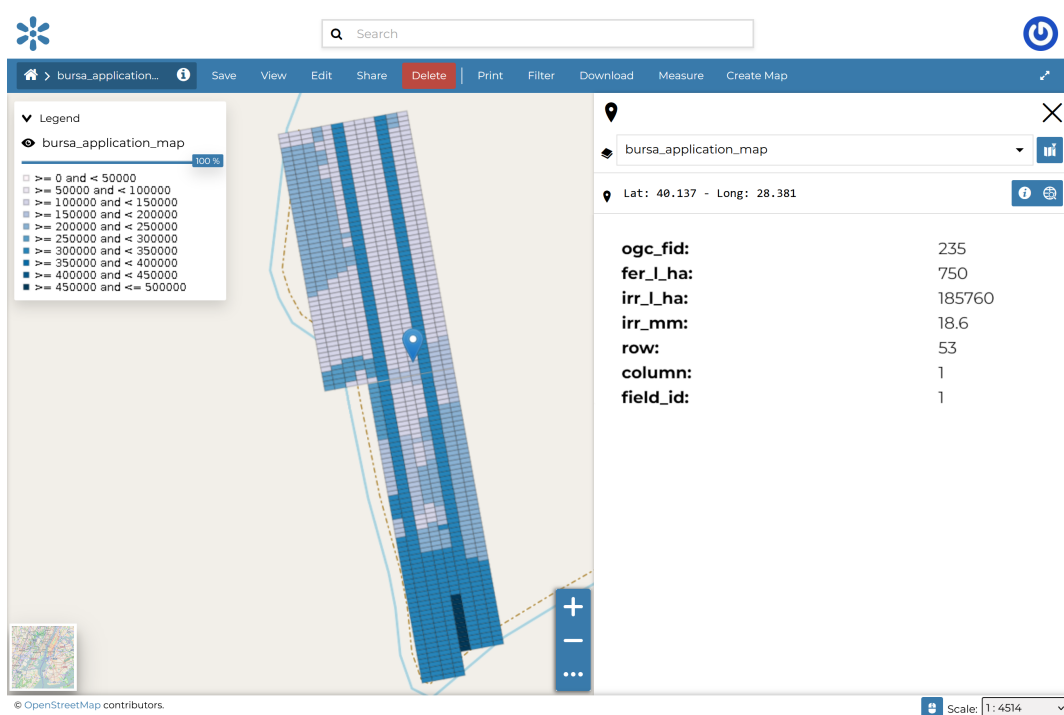


FIGURE 7.8: Fertigation recommendation map for Field 3 in Turkey as displayed in the geoportal.



FIGURE 7.9: Boom of the HIS during the field trial in Field 3, Turkey, on 24 August 2023, showing the mounted 300 L fertilizer tank and the supply lines for the four boom sections.



FIGURE 7.10: Reel section of the HIS during a different field trial in Turkey.

Chapter 8

Discussion and Outlook

8.1 Discussion

This work demonstrated that a cloud-based SDI, combined with a DSS and an in-field sensor network, can be effectively integrated with a VR-capable HIS into a data-driven platform for site-specific fertigation. Furthermore, the thesis illustrates how open-source geospatial technologies (GeoNode, PostGIS, OGC-services) can form the backbone of next-generation farm ICT systems for PA.

The ADDFerti solution follows the general trend of shifting processing and storage tasks from on-site devices to cloud-based infrastructures (Beyer et al., 2025). This architecture enables simpler and more cost-efficient hardware in the field, while computational and storage resources are centralized in the cloud, where they can be scaled and maintained more efficiently. The scalability of this approach was demonstrated in practice by expanding the DSS to different test sites in Belgium, Germany, and Turkey with minimal configuration effort.

Potential of SDIs for Variable Rate Applications in Precision Agriculture

A major barrier to the wider adoption of PA remains the insular nature of existing ICT systems, in which software, sensors, and applications often operate in isolation. This lack of interoperability has been noted in earlier studies (Nash et al., 2009; Korduan et al., 2004) and continues to hinder seamless data exchange until present day (Roussaki et al., 2023; Palma et al., 2022). Several authors have highlighted the potential of SDIs to overcome these barriers by providing a unifying framework for standardized data access and integration in PA (Jackenkroll, 2021; Korduan et al., 2004). In this context, OGC web services play a crucial role for PA by defining open standards (Nash et al., 2007; Nash et al., 2009).

A key advantage of SDIs is their scalability across different spatial and organizational levels. Even at small experimental scales, SDIs inherently provide essential components such as standardized interfaces (WMS, WFS, WCS), spatial databases, metadata management, and user access control; all of which would otherwise require complex, custom-built solutions. While platforms such as CKAN or GeoNode are primarily designed for manual upload and download of spatial data, this work demonstrated that automated

data transmission is equally feasible using their existing interfaces (e.g., REST for data upload and WFS for data retrieval). The SDI in ADDFerti served as a real-time communication hub between all system components.

Not only were the resulting datasets (e.g., application maps) made available online, but also the intermediate and input data, such as soil moisture measurements, weather information, and MZ layers, were automatically published within the SDI. This approach enhanced data traceability throughout the workflow and, in turn, improved process transparency and facilitated error detection, for instance in the identification of mismatched MZ identifiers when generating application maps. In general, this strategy enables the generation of additional knowledge and applications from data that would otherwise remain hidden within individual processing steps, such as through the creation of analytics, monitoring dashboards, or supplementary decision support systems.

One possible perspective for the further development of SDI is the integration of real-time remote sensing data streams. This could be realized through the use of Sentinel Hub¹), which provides access to Earth observation data from major satellite missions via both a graphical web interface and standardized OGC services such as WMS, WCS, WFS, and WMTS. A particular advantage of Sentinel Hub is that, in addition to its standard data catalogue with predefined OGC endpoints, it also allows the creation of customized endpoints that can include server-side processing operations. This enables users to directly retrieve derived (analysis ready) products; for example, the mean NDVI of each pixel for a specified area and time period (e.g., the past two weeks). Incorporating such services into the SDI, and subsequently into the DSS, would enable the generation of dynamic MZs for fertilization (Uribeetxebarria et al., 2022) and could also support irrigation prescriptions in cases where in-situ soil moisture data are unavailable (Chakhar et al., 2024).

Suitability of Different Irrigation Systems for VRFI

In large-scale arable farming, the suitability of irrigation systems for VRI or VRFI depends mainly on technical design and economic feasibility. Stationary systems are generally more complex and expensive than travelling systems, as each emitter or section irrigates a fixed area and requires its own control unit. Implementing VRFI would further demand dedicated fertilizer lines to deliver nutrients directly to move the nutrient injection points directly to each section or emitter, resulting in highly complex and costly installations.

Travelling systems such as center-pivot, lateral-move, and hose-reel irrigation platforms are therefore better suited for VRFI. Their continuous movement across the field allows each controllable emitter (e.g. sprinkler) or section to cover a larger area, reducing the number of control units required.

All three travelling systems can in principle be upgraded for VR operation. The choice depends on field geometry, topography, investment capacity, and

¹<https://docs.sentinel-hub.com/api/>

equipment availability. Center-pivot and lateral-move systems are fixed installations that offer high efficiency and low operating costs but require large upfront investments and are limited to fields of suitable shape and slope. Hose-reel systems, by contrast, are mobile and can be deployed across multiple fields or crops within a rotation, offering greater flexibility for farming systems with variable irrigation demands.

Input Data for Map-Based VRFI

For map-based systems, the accuracy of fertigation prescriptions maps depends primarily on the quality and resolution of the input data used to delineate MZs. A practical approach is to combine existing or freely available datasets. RS data, such as from Sentinel-2, are freely accessible and provide consistent spatial and temporal coverage. Yield data are also commonly collected as part of standard farm operations. Additional sources of spatial variability include topography, historical land use, and fine-scale weather patterns, all of which influence soil moisture, nutrient dynamics, and crop growth.

Soil, however, remains the most complex and heterogeneous component of the production system (Nawar et al., 2017). Generating high-resolution soil maps requires precise sensor equipment and dense sampling grids. Systems such as the on-line multi-sensor platform provided by UGent can provide detailed soil information, whereas novel devices like the handheld Stenon FarmLab still face challenges in measurement accuracy and achievable sampling density within a reasonable timeframe (Steiger et al., 2025). Nevertheless, innovative sensing technologies and devices can and will make soil sensing more accessible and economically feasible in the future.

Sensor-Based VRFI Using On-Board Sensors

An interesting future direction would be the development of a sensor-based system for VRFI that relies on real-time, on-board sensing. Such an approach would be particularly well suited for HIS, which are mobile and can be operated across multiple fields. In contrast to map-based systems that require prior field campaigns for MZ delineation and prescription map generation, a sensor-based solution could operate autonomously and adjust application rates dynamically during operation. The objective would be to create a fully integrated turnkey device. For the fertilization component, commercially available systems such as the Yara N-Sensor could be incorporated to provide real-time nutrient recommendations.

For soil moisture monitoring, several emerging proximal and non-invasive sensing technologies could be employed (Hardie, 2020). Proximal sensors operate on or near the soil surface and can be mounted on (agricultural) vehicles to produce spatially continuous maps of soil moisture variability. Potential sensing methods include cosmic-ray sensors (McJannet et al., 2017), electromagnetic induction (EMI) (Doolittle and Brevik, 2014), portable optical spectroscopy (vis-NIR and NIR), and ground-penetrating radar (GPR) (Klotzsche et al., 2018).

The main advantage of such sensors is their ability to overcome the limitation of traditional in-situ probes (e.g., FDR sensors), which are stationary and can measure only small soil volumes. However, non-invasive approaches also present several challenges (Hardie, 2020). These include limited or variable penetration depths depending on soil moisture conditions (e.g., GPR, EMI, cosmic-ray, and microwave sensors), difficulties in separating signals originating from different soil layers, and large measurement footprints for some methods, such as cosmic-ray sensors, which typically integrate over areas with a diameter of around 100 m (Döppler et al., 2022). In Wu et al. (2022), GPR-based soil moisture mapping showed promising results, including mounting the system on a mobile VR irrigation device, demonstrating its potential for on-the-go sensing in operational systems.

8.2 Recommendations for further research

While this work demonstrated the feasibility of an data-driven VRFI system, several opportunities and recommendations for further research were identified:

1. **Quantitative evaluation of VRFI performance.** Multi-season trials under diverse conditions are needed to quantify the agronomic, economic, and environmental effects of VRFI by using life cycle assessment and cost–benefit analyses.
2. **Further testing of the HIS hardware.** Although not directly part of this work, system tests over multiple seasons are needed to reveal eventual weak points in the VRFI hardware. This included evaluating the mechanical robustness of the VR components, the performance and calibration of the injection system and the flow sensors, as well as the overall usability of the system.
3. **Advancement of the SDI.** Extending the cloud-based SDI with real-time remote sensing data streams (e.g., Sentinel Hub OGC APIs) would enable dynamic MZs that evolved throughout the growing season. More generally, on a policy level, promoting interoperability between SDIs and external platforms would support broader data sharing and integration. This can be achieved through the use of open-source software, open data principles, and standardized interfaces.
4. **Advancement of the DSS.** Integrating crop growth models into the DSS would allow a more accurate adjustment of fertigation rates throughout the season.
5. **Exploring novel soil and crop sensing approaches.** Further research should investigate the use of advanced sensing techniques and sensor fusion, which could ultimately culminate in the development of a fully sensor-based fertigation system.

Chapter 9

Conclusion

This dissertation presented the design, implementation, and validation of an integrated information and communication technology (ICT) infrastructure for variable rate fertigation (VRFI) in arable farming based on a hose-reel irrigation machine (HIS). The work was conducted within the framework of the European ICT-AGRI-FOOD project ADDFerti and demonstrated how concepts from precision agriculture (PA), spatial data infrastructures (SDI), sensor networks, and decision support systems (DSS) can be combined into a coherent system for information-driven irrigation and fertilization.

At the core of this system was a modular, cloud-based SDI that enabled the exchange, storage, and publication of geospatial and sensor data in standardized, interoperable formats. The SDI was mainly implemented via a geoportal using the open source GeoNode software and served as the central communication hub between the sensor network, the DSS, and the HIS. One of the main reasons for choosing GeoNode was its thorough use of open standards and interfaces. For publishing geospatial data layers, the SDI offered OGC services (WMS, WFS, and CSW), which were used by the other components (DSS, HIS) to access the hosted data. Automatic data upload was possible via external Python scripts through a well-documented REST interface, as well as manually through the web interface. The SDI provided a flexible foundation that offered open, scalable, and standards-based geospatial data management, which was essential for the ADDFerti VRFI solution and may also be used in future VRFI systems.

A second major component of this research was the automatic DSS for fertigation, implemented as cloud-based Python scripts that retrieved, processed, and integrated heterogeneous data streams to calculate site-specific VRFI application maps. One of the key inputs were the management zones (MZs), which were delineated on the basis of soil, crop, and topographic attributes, supplemented by field geometry. Furthermore, the DSS used real-time soil moisture data from LoRaWAN-based soil moisture sensors to obtain point-based live status of the field's soil moisture conditions. The sensor network, including the workflow for the automatic retrieval of soil moisture data, was also developed as part of this work. Weather data were integrated through the API of an external open-weather service, and soil water-holding properties (FC, PWP) were included as additional inputs. The resulting fertigation maps were generated in less than 30 s and published directly to the SDI, ensuring seamless availability for the HIS.

For the irrigation component, the methodological approach for creating VRFI recommendations could therefore be characterized as a hybrid of map-based and sensor-based decision-making, in which static map-based information was enriched with live soil moisture sensor and weather data to dynamically adjust irrigation rates within the MZs. By contrast, the fertilization component was entirely map-based.

The third major component was the validation of the integrated system under real-world conditions during the fertigation trials in Karacabey, Turkey. These experiments confirmed the end-to-end interoperability of the ICT components, including the LoRaWAN sensor network, the SDI-based data exchange, the DSS logic, and the HIS control software. Fertigation maps generated by the DSS were successfully retrieved by the HIS and applied during the field operations, demonstrating that the fully automated sensor-to-actuator workflow is technically feasible at field scale.

Beyond the specific application in the ADDFerti prototype, the conceptual advances of this work are transferable. The SDI and DSS were designed to be hardware-independent and can integrate additional sensor platforms, alternative irrigation and fertilization systems, or other VR workflows. The approaches developed in this work (e.g., the delineation of MZs, the data fusion of real-time and static parameters, and the creation of application maps) follow principles that are applicable across a broad range of PA contexts. This flexibility makes the proposed architecture relevant not only for VRFI but also for variable rate irrigation (VRI), variable rate fertilization (VRF), and other sensor-driven site-specific PA operations.

The dissertation also highlighted the significance of open standards and reproducible workflows in modern agricultural ICT systems. By relying on OGC standards for data access and service provision, and by adopting open-source tools for data processing and visualization, the system supported transparent, traceable, and interoperable data flows. These characteristics were essential for future integration with FMIS platforms, commercial machinery, and larger-scale geodata infrastructures. The publication of all scripts and code produced for this work under open and free licences guarantees reproducibility and enabled adaptation by researchers, developers, and stakeholders in the wider PA community.

In conclusion, this dissertation provided a coherent conceptual and technical framework for information-driven fertigation in PA. By combining sensor networks, standardized SDI components, and automated DSS algorithms, the work bridged the gap between spatial data analysis and operational VRFI control. The results demonstrated that map-based fertigation, enhanced through live sensor data, could be implemented in a fully automated manner on customized farm-scale equipment. The developed approach supported efficient resource use, enhanced transparency in agricultural data workflows, and laid the foundation for future research and innovation in data-driven water and nutrient management.

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Declaration of Authorship

I, Alexander STEIGER, hereby declare that this dissertation entitled “Spatial Data Infrastructure and Algorithms for Variable-Rate Fertigation in Precision Agriculture” is my own work. I have written this thesis independently and have used no sources or aids other than those explicitly indicated. All passages that are taken directly or indirectly from other sources are clearly identified as such. This dissertation has not been submitted, in whole or in part, to any other examination board or institution for the purpose of obtaining an academic degree.

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