UNIVERSITÀ DEGLI STUDI DI PADOVA

Department of Agronomy Food Natural Resources and Environment

Second Cycle Degree (MSc)
in
Sustainable Agriculture

Comparative analysis between fixed and variable rate nitrogen applications in open-field borettana cultivation

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Academic Year 2023-2024

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Abstract

Precision agriculture methods have gained prominence in optimizing crop production through customized fertilization practices. This study delves into the refinement of nitrogen (N) fertilizer application strategies for Borettana onion cultivation in open fields. It explores a comparative analysis between fixed and variable rate nitrogen applications, employing advanced remote sensing techniques, such as Normalized Difference Vegetation Index (NDVI) imagery derived from unmanned aerial vehicles (UAVs), in conjunction with field surveys. By comparing the actual crop status at a fine spatial and temporal resolution with optimal vegetation conditions (theoretical) from previous experiments, prescription maps of N fertilization were compiled for field applications and crop growth ad yield response finally evaluated. The experimental setup encompassed 20 plots, each replicated five times (with two sub-replications), incorporating four distinct levels of N application. These included two fixed-rate N regimes in 5 top-dressing application: _140 (220.5 kg N ha-1 yr-1) and _90 (168 kg N ha-1 yr-1), as well as two variable-rate schemes that derived from a fixed high- and low-starting input followed by 4 variable rates (totally 5 top-dressing applications): VRA_A and VRA_B. Over the course of the crop cycle, multispectral UAV imagery was employed to generate NDVI maps at multiple time intervals, facilitating insights into the dynamics of crop growth and N uptake. Concurrently, field surveys were conducted to monitor crop biomass production, growth patterns, and soil N dynamics for further ground-truth validation of remotely sensing outputs.

NDVI mapping effectively detected variations in onion growth throughout the cropping season, aiding in the definition of variable rate N applications that were in between (from 180 to 195 kg N ha-1 yr-1) the high (220.5) and low (168) fixed doses. Despite such differences, the findings of this study indicated that there were no significant differences in onion bulb biomass among the treatments at harvest, while some enhancement in the nitrogen use efficiency (NUE) was found close to statistical significance ($p = 0.06$).

In summary, this thesis offers a comprehensive comparative analysis of fixed and variable rate nitrogen applications in open-field Borettana onion cultivation. By synthesizing empirical observations, remote sensing data, and analytical methodologies, the study provides a valuable resource for informed decision-making in precision farming practices. The insights derived from this research have the potential to reshape nitrogen fertilization strategies, fostering sustainable and efficient crop production systems. Further studies are suggested to better identify the optimal N fertilizer application during the growing season and to identify the most appropriate time of fertilizer application that can better synchronize crop

demands and application rates. Finally, some improvement might be related to modelling approaches that are better suited to identify yield potentials in homogeneous field areas.

1. Introduction:

1.1. Contemporary Agricultural Challenges

Human progress is characterized by a sequence of modifications directed towards advancement, with these transformations being carefully structured in accordance with established standards (Yulihastin et al., 2011). At its core, progress targets economic expansion and the enhancement of human life quality in a more favorable trajectory. The agricultural domain serves as a catalyst for development, furnishing raw materials, employment prospects, nourishment components, and buying power for goods generated by other sectors. Particularly, the realm of agriculture in all its sectors, is still substantial contributor to the economic growth and overall regional economic output (GRDP) of every locality (Sitanggang, 2015).

Notably, the demand for environmental sustainability spans globally, and this mandate unavoidably influences policies related to the application of chemical inputs and substances that bear adverse consequences on the environment (Anugrah et al., 2014).

Contemporary agriculture confronts a paramount challenge - harmonizing the soaring demand for food production with the imperative to mitigate its pervasive environmental repercussions. The unchecked expansion of human activities, catalyzed by globalization and climatic shifts, has intensified the urgency to cultivate resource efficiency and ecological sustainability as central tenets (Almond, 2020).

Fertilizers play a vital role in enhancing crop yield and contributing to global food security[1]. However, improper management and excessive use of commercial fertilizers can result in reduced efficiency of nutrient utilization, along with the accumulation and depletion of nutrients from the soil. Leaching, a process in which ions are released into soluble forms and carried by percolating water, is in many areas of the world a concern, together with other fluxes that can have great impact in the environment, such as emission of greenhouse gasses (CO2, CH4 and N2O), soil degradation and loss of biodiversity. The extent of nutrient loss through leaching is determined by the concentration of elements in the soil and the volume of water drained. The issue of nutrient leaching has gained significant attention due to its potential to move nutrients beyond the root zone, leading to immediate nutrient loss for crops and economic setbacks for farmers. The application of nutrients to the soil undergoes a complex series of transformations driven by various physical, chemical, and biological processes, rendering them accessible to crops but also susceptible to leaching-induced losses[2].

The process of soil nutrient leaching is influenced by a multitude of factors, encompassing soil composition, the presence of available nutrients, precipitation volume and intensity, irrigation frequency, and the specific crop under cultivation. Among the nutrients susceptible to leaching, nitrogen is among the most impactful because of its high mobility, posing significant environmental challenges (e.g., eutrophication) and gives rise to potential hazards to human well-being[3].

The excessive utilization of fertilizers leading to subsequent health and ecological concerns has been acknowledged as a significant environmental predicament associated with agriculture across numerous regions globally[4].

1.2. Nitrogen and nitrate dilemma

Nitrogen (N) stands as a pivotal nutrient for fostering robust plant growth. The advent of the Haber-Bosch process during the early 1900s marked a watershed moment, enabling the mass production of synthetic N fertilizers and heralding a remarkable surge in crop yield. This breakthrough, however, set in motion a trajectory of escalating global N fertilizer usage, surging from 11.3 Tg N/year in 1960 to a staggering 107.6 Tg N/year by 2013[5].

While the advent of synthetic fertilizers has undeniably propelled crop productivity to unprecedented heights, its huge amount into the agroecosystems has significantly affected the tradeoff between inputs and outputs. Moreover, the efficient use of nitrogen by crops (Figure 1) is far from the theoretical and desirable unit, with global estimates of nitrogen use efficiency (NUE) of merely 0-42-0.45 taken up by crops (Udvardi et al., 2021)[6].

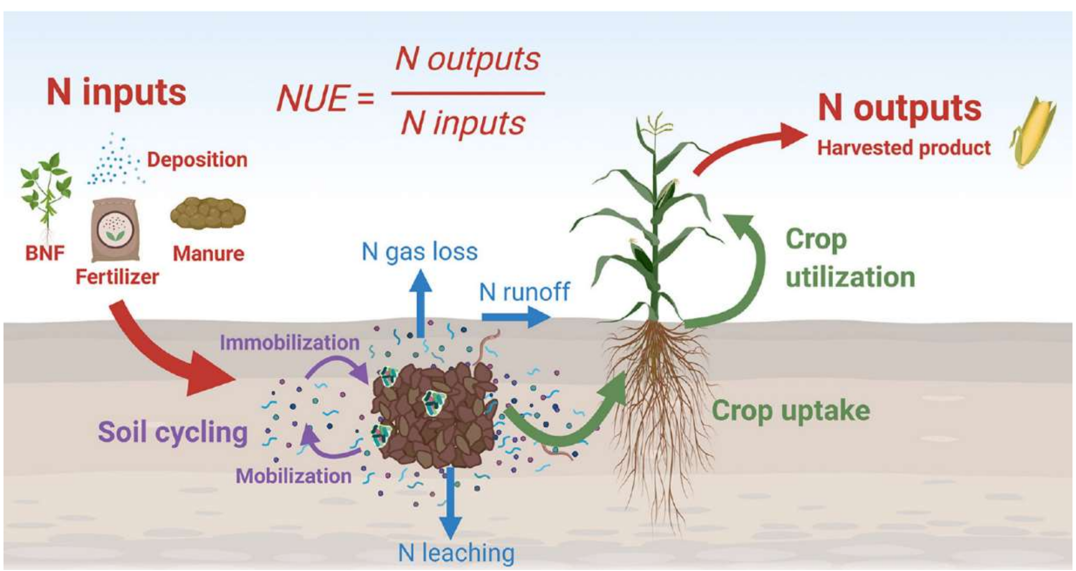

Figure 1 Nitrogen use efficiency (NUE) is the ratio of N outputs in the harvested product to N inputs, including from fertilizer and natural processes, and has also been called N removal efficiency. Nitrogen inputs to the system (red arrow, BNF is biological nitro

The surplus fertilizer, lingering in the soil and infiltrating groundwater or emitted into the atmosphere as nitrous oxide or ammonia, triggers a cascade of ecological predicaments. Eutrophication, emissions of greenhouse gases, soil acidification, and the proliferation of NO3-N pollutants in both surface water and groundwater emerge as formidable environmental predicaments stemming from this surplus[7].

As N fertilizers traverse the unsaturated zone, excessive N undergoes swift conversion into NO3− through the process of nitrification. Given the water-soluble nature of NO3 and its limited propensity for soil particle adsorption, its presence in an aquifer system raises concerns about prolonged water quality deterioration. In the quest to comprehend this intricate interplay, numerous investigations have scrutinized the contamination of groundwater by NO3 originating from N fertilizers. These inquiries encompass the evaluation of the N budget, the assessment of N leaching through soil, and the estimation of groundwater's vulnerability to NO3-N through the deployment of age tracers. It follows that the excessive application of N fertilizer or its wrong application without knowing the spatial characteristics of crops and soils directly exacerbates the predicament of groundwater and surface water pollution attributed to elevated levels of NO3-N[8].

1.3. Precision Agriculture

The International Society of Precision Agriculture (ISPAG) characterizes precision farming as a comprehensive management approach that collects, processes, and analyzes temporal, spatial, and individual data, integrating it with other relevant information to facilitate management decisions. This methodology aims to enhance resource utilization efficiency, productivity, quality, profitability, and the sustainability of agricultural production by accounting for estimated variability[9].

Against the backdrop of escalating global demands for agricultural production and the imperative for sustainable resource utilization, the notion of precision agriculture has emerged as a revolutionary remedy[10].

Precision agriculture revolves around the profound ability to scrutinize spatial variations within the soil, comprehending their intricate influence on the variability of crops. This understanding paves the way for the meticulous implementation of management strategies tailored to specific needs. The domain of precision agriculture encompasses a vast spectrum of factors, including the diverse facets of soil resources, dynamic weather conditions, intricate plant genetics, diverse crop varieties, optimal machinery efficiency, and the intricate interplay of physical, chemical, and biological inputs that contribute to the intricate tapestry of crop production.

In the midst of this intricate framework, the concept of precision agriculture emerges as a guiding light, providing tailored strategies that align with the unique requirements of individual agricultural parcels. This paradigm shift aims to finely calibrate resource allocation, enhance yields, and minimize the environmental impact[11].

Precision agriculture refers to a method of crop management in which specific areas of land or crops within a field are treated with varying levels of input. This approach offers several potential advantages:

1. Enhanced Economic Returns: Precision agriculture holds the promise of increasing economic returns from crop production through improved yields or reduced inputs.

2. Environmental Protection: By avoiding excessive application of agrochemicals that can harm the environment, precision agriculture can contribute to minimizing the risk of environmental pollution.

3. Enhanced Accountability: Precise targeting and meticulous recording of field applications enhance traceability, ensuring a higher level of accountability in farming practices.

These benefits provide compelling instances where economic and environmental considerations intersect harmoniously[12].

In the last ten years, commercial availability of technology has empowered farmers to spatially document field yields and field variability with high precision, even with on-the-go sensors that overcome costly and time-consuming groud-truth measurements (Murphy et al., 1995; Birrell et al., 1996; Stafford et al., 1996), and tailor seed and fertilizer rates according to site-specific requirements. Noteworthy progress has been achieved (Miller & Paice, 1998), for instance, in enabling the spatial control of weed populations based on their density, by adjusting herbicide dosages, or by providing nutrients to vegetation based on their potential crop growth. However, the advantages stemming from potential yield increments and decreased dependence on fertilizers and agrochemicals must be weighed against the investment costs associated with specialized equipment required for generating yield maps and implementing variable applications.

Within these frameworks, remote and proximal sensing methodologies offer a range of solutions for data collection and production mapping. Among the available platforms, which exhibit variances in spatial and temporal resolution, both satellites and the most recent unmanned aerial vehicles (UAVs) are widely employed in precision agriculture applications[13].

1.4. Technologies in precision agriculture

Agricultural production systems have reaped the rewards of integrating technological breakthroughs that were initially developed for other sectors. The mechanization and synthetic fertilizers of the industrial era and the genetic engineering and automation of the technology age have significantly impacted agriculture. In the current information age, there is a promising potential to incorporate technological advancements into PA (Whelan et al., 1997).

The foundational premise of PA, which involves the recognition of spatial and temporal variations in soil and crop conditions within a field, has been acknowledged for centuries. In the era before complete agricultural mechanization, the relatively small field sizes enabled farmers to manually adjust treatments based on these variations. However, as fields expanded in size and mechanization intensified, addressing within-field variability has become progressively more challenging without revolutionary technological advancements (Stafford, 2000).

The concept of PA is framed within a systemic approach aimed at restructuring the entire agricultural system towards a model of low-input, high-efficiency, and sustainable agriculture (Shibusawa, 1998). This innovative approach leverages the convergence of various technologies, such as the Global Positioning System (GPS), geographic information system (GIS), compact computer components, automated control mechanisms, in-field and remote sensing capabilities, mobile computing, advanced data processing, and telecommunications (Gibbons, 2000). The agricultural sector has gained the capacity to gather more comprehensive data on spatial and temporal production variability. Consequently, the aspiration to effectively address this variability at a fine scale has become the primary objective of PA (Whelan et al., 1997).

After more than a decade of evolution, precision agriculture has reached a pivotal juncture where much of the required technology is accessible, but the actual environmental and economic advantages remain unproven (Stafford, 2000). While numerous technological advancements have been introduced, the development of agronomic and ecological principles to formulate optimized input recommendations at the localized level is still somewhat behind. Many farmers are grappling with the decision of whether to integrate available PA technologies into their operations. The impetus for the widespread adoption of PA technologies could stem from stringent environmental regulations, public apprehensions regarding excessive agrochemical usage, and the potential economic benefits associated with reduced agricultural inputs and enhanced farm management efficiency. Ultimately, the success of PA technologies will be gauged by their ability to deliver both economic prosperity and environmental enhancements[14].

The implementation of precision agriculture heavily relies on cutting-edge technologies that allow for targeted and site-specific agricultural management. These technologies encompass a range of tools, from advanced computing systems to remote sensing devices, each playing a crucial role in optimizing resource allocation, improving productivity, and mitigating environmental impact.

1.4.1. Computers

After over a decade of extensive research and practical implementation, precision agriculture has amassed a substantial volume of data, leading to a significant challenge known as 'data overflow'. The vast spatial and temporal information that has been gathered calls for the development of dedicated tools tailored to tasks such as data storage, processing, management, and analysis. Moreover, there is a pressing requirement for the standardization of data exchange protocols in order to facilitate seamless communication and integration among various PA systems and stakeholders[15].

Computational advancements are at the core of precision agriculture. Modern computers enable the processing and analysis of vast amounts of data collected from various sources, such as sensors and remote sensing devices, despite the principle of precision agriculture can be theoretically applied even without any technology advancement. Anyway, complex algorithms are usually employed to interpret these data, providing insights into factors such as soil composition, nutrient levels, weather conditions, and plant health. These insights are then utilized to make informed decisions about resource allocation and management strategies.

1.4.2. Global Positioning System (GPS)

The Navigation Satellite Timing and Range Global Positioning System (NAVSTAR GPS) is a satellite-based radio-navigation system renowned for its capacity to furnish remarkably precise worldwide, continuous, three-dimensional location data encompassing latitude, longitude, and elevation. This system, designated as GPS, was conceptualized and is overseen by the US Department of Defense (DoD), functioning as an accurate and all-weather navigation system. Despite its military origins, GPS is accessible to civilians under certain limitations, primarily for positioning purposes. A constellation of at least 24 satellites meticulously positioned in Earth's orbit, forming a meticulously designed pattern, has brought GPS to full operational capability (Gelian et al., 2012).

GPS technology manufacturers have devised a range of tools aimed at augmenting the efficiency and productivity of farmers and agribusinesses in the domain of precision farming. In contemporary practice, many farmers leverage GPS-derived products to optimize their operational activities. These products capture location data through GPS receivers, which proves beneficial for creating maps of field boundaries, roads, irrigation networks, and areas with crop-related issues such as weed infestations or disease outbreaks. GPS's accuracy empowers farmers to generate precise farm maps outlining field acreage, road alignments, and distances between points of interest. By leveraging GPS, farmers can precisely navigate to designated field locations across successive seasons, facilitating tasks like soil sampling and crop condition monitoring (Qian and Zheng, 2006).

Global Positioning System (GPS) technology is a cornerstone of precision agriculture, enabling accurate location tracking and spatial mapping within agricultural fields. With the aid of GPS, farmers can precisely determine the position of vehicles, machinery, and other resources, facilitating tasks such as seeding, fertilization, and pesticide application according to predefined coordinates.

Figure 2 Topcon Hiper pro GPS (left) and T-GIS Handheld Controller (right).

1.4.3. Geographic Information Systems (GIS)

Geographic Information System (GIS) is a comprehensive tool that facilitates the collection, management, analysis, and presentation of geospatial data. It encompasses a broad range of applications, from mapping and spatial analysis to decision-making support across various fields.

While general-purpose GIS software packages such as ArcView, IDRISI, and SURFER offer a multitude of functions, some of these functions might hold limited relevance for Precision Agriculture (PA) applications. Additionally, these packages often come at a considerable cost and necessitate computer platforms that are not typically accessible to farmers. Recognizing the imperative for PA applications at the field level, several commercial GIS software packages have been developed by entities like AGRIS Corporation, Farm WorksTM, AgriLogic, Inc., John Deere Precision Farming Group, Case Corporation, Rockwell International, and RDI Technologies, Inc. These commercial packages are designed to cater to the specific requirements of PA, allowing for more effective implementation on a practical level (Ess et al., 1997). Some of these systems even interface directly with Differential Global Positioning System (DGPS) devices or yield sensors, enabling real-time acquisition of location and yield data. A notable example is the development of a field-level GIS (FIS) by Runquist et al. (2001), which incorporates analytical functions tailored for spatial data analysis within the context of PA research. This convergence of GIS technology with PA aims to enhance precision, efficiency, and informed decision-making in agricultural practices[16].

Off-the-shelf GIS software, including widely recognized options like ArcView, IDRISI, and SURFER, often comes with an array of functions that may not always align well with precision agriculture needs. Moreover, these packages tend to be costly and demand computer platforms that may not be readily accessible to farmers. Recognizing the demand for PA applications tailored for on-field use, numerous commercial GIS software solutions have been developed. Notable examples include software packages from AGRIS Corporation, Farm WorksTM, Agri-Logic, Inc., John Deere Precision Farming Group, Case Corporation, Rockwell International, and RDI Technologies, Inc. Some of these systems are designed to interface directly with differential global positioning system (DGPS) devices or yield sensors, enabling real-time acquisition of location and yield data. In a similar vein, Runquist et al. (2001) crafted a field-level GIS (FIS) that incorporates analytical functionalities for spatial data analysis within the context of PA research[17].

Geographic Information Systems (GIS) play a pivotal role in integrating spatial data, allowing farmers to create detailed maps that depict variations in soil properties, nutrient distribution, and crop growth within a field. These maps aid in decision-making by highlighting areas that require specific interventions, such as adjusting fertilizer application rates or irrigation schedules.

1.4.4. Sensors

Sensors serve as electronic devices that respond to various physical stimuli, including heat, light, magnetism, motion, pressure, or sound, by generating an impulse. These devices have been designed to measure a wide spectrum of factors, encompassing machinery, soil properties, plant conditions, pest presence, atmospheric attributes, and water parameters. They achieve this by detecting and interpreting signals such as motion, sound waves, pressure changes, mechanical strain, temperature variations, light intensity, and magnetic fields. These signals are then correlated with specific properties like reflectance, resistance, absorbance, capacitance, and conductance.

The integration of sensors is of paramount significance in the realm of precision agriculture. Their role is pivotal for the establishment of a precision agricultural system, primarily due to three compelling reasons:

1. Fixed Costs: Sensors offer the advantage of predictable costs. Once acquired, their financial outlay remains relatively stable, contributing to a more predictable budgetary allocation.

2. Microscale Sampling: Sensors have the capacity to capture data at exceptionally minute spatial and temporal scales. This capability is essential for achieving a granular understanding of the agricultural environment.

3. Repetitive Measurements: Sensors facilitate the collection of data through repetitive measurements. This capability is instrumental for tracking changes over time and making informed decisions based on evolving conditions.

In the domain of precision agriculture, the role of sensors is indispensable due to the extensive data collection, coordination, and analysis required. This data serves a dual purpose - for strategic surveys and inventories, as well as for real-time applications. By harnessing the potential of sensors, precision agriculture aims to optimize resource utilization, improve decision-making, and enhance overall agricultural efficiency (Sudduth et al., 1997). This dynamic synergy of sensors and agricultural practices underscores the value of data-driven precision in modern farming (Pierce & Nowak, 1999).

1.4.5. Proximal Sensing

Proximal sensing and remote sensing stand out as two primary techniques employed for gathering information about objects or phenomena without the need for physical contact, forming the bedrock of technologies extensively utilized in precision agriculture. Remote sensing is closely associated with satellite or aerial platforms, utilizing multi- or hyperspectral imagery. Proximal sensing, on the other hand, involves sensors situated in close proximity to the object under scrutiny, and these sensors find placement across a spectrum of platforms, ranging from handheld devices and fixed installations to robotic and tractor-embedded systems. Unmanned aerial vehicles (UAVs), often referred to as drones, occupy a position between remote and proximal sensing since they are at a moderate distance from the target object, a characteristic that places them within the realm of both remote and proximal sensing.

The utilization of these technologies entails either on-the-go sensors mounted on agricultural machinery or handheld instruments that facilitate site-specific management activities, such as variable rate applications (Christy, 2008). Thanks to their high sampling density, these sensors offer enhanced capabilities in capturing field variability, thus effectively addressing the challenge of selecting a suitable soil sampling strategy to ensure representative soil samples. Assessing sensor accuracy entails evaluating measurement repeatability at consistent times and locations, alongside correlating reference measurements of soil properties (Sinfield & Fagerman, 2010).

While the potential of in situ soil reflectance spectroscopy applications is promising, their successful implementation requires optimal environmental conditions and various pre-treatment methods to counteract the influences of factors like moisture content, soil surface irregularities, and vegetation coverage (Gehl & Rice, 2007). Incorporating proximal soil sensing techniques holds the potential to enhance the volume of measured soil samples necessary for a comprehensive understanding of soil heterogeneity on a field scale. To this end, researchers have been actively engaged in refining or upgrading existing sensors (Waiser & Morgan, 2007). Realizing successful measurements through proximal sensing could offer significant advantages for agriculture. These measurements play a role in delineating management zones and facilitating the fine-tuned control of input applications in the environment through the application of precision agriculture techniques (Sarkhot & Grunwald, 2011).

1.4.6. Remote Sensing

The integration of remote sensing techniques into precision agriculture has been limited due to the requirement for images with high spatial resolution. Recent literature indicates that remotely sensed images have been applied to various aspects of agricultural management. For instance, these images have been utilized to forecast nitrogen requirements in corn (Scharf and Lory, 2000), to estimate cotton lint yield (Li et al., 2000; Hendrickson and Han, 2000), to evaluate insect damage in wheat (Riedell et al., 2000), to identify spider mite infestations in cotton (Fitzgerald et al., 2000), to aid in insecticide application (Seal et al., 2000), to approximate the clay concentration of surface soil (Chen et al., 2000), to detect weeds (Varner et al., 2000), to quantify hail or wind damage in crops (Erickson et al., 2000), and to identify and classify anomalies or unusual occurrences (Carter and Johannsen, 2000).

While satellite-based remote sensing holds considerable potential for in-field monitoring, its definitive success has yet to be conclusively established. Challenges encompass factors such as the timeliness of data acquisition, cloud cover interference, costs, suboptimal spatial resolution, and the necessity for image data processing that aligns with the needs of crop managers[18]. Hyperspectral sensing is an emerging technology that provides information across a nearly continuous spectrum in the visible, near-infrared (NIR), and mid-infrared (MIR) wavebands. Hyperspectral sensor-derived images have been employed for assessing crop vigor and predicting yields, distinguishing between crops, weeds, residue, and soil, and quantifying crop water content and leaf area index. The MIR band has the potential to offer insights into plant nutrient status and soil properties as well (Deguise and McNairn, 2000).

1.4.6.1. Unmanned Aerial Vehicles (UAVs)

Unmanned aerial vehicles (UAVs), commonly referred to as drones, have become increasingly accessible due to their affordable pricing and offer the capability to capture ground data accompanied by precise geographic coordinates. This functionality empowers users with a comprehensive and clearer depiction of ground-related information. Notably, drones equipped with multispectral and RGB cameras extend the advantage of imaging the near-infrared spectrum over crops, thereby furnishing insights into the health conditions of crops.

The integration of drone-generated images and ground sensor data is anticipated to play a pivotal role in the domain of precision agriculture (PA) (Daponte & De Vito, 2019). In the agricultural context, drones hold the potential to deliver real-time imagery and sensor data from farm fields that might be challenging to access swiftly on foot or using conventional vehicles (Malveaux, 2014).

1.4.6.2. Normalized Difference Vegetation Index (NDVI)

Vegetation indices (VIs) often arise from mathematical relationships between reflected light in the visible and near-infrared (NIR) wavelengths. These indices offer a straightforward approach for assessing plant responses. Among them, the Normalized Difference Vegetation Index (NDVI) stands out as the most widely used and highly correlated one. NDVI is specifically designed to identify variations in green canopy area, with an emphasis on the healthy green color of crops. Its derivation from satellite images worldwide has proven effective in detecting long-term land-use/cover changes and in modeling terrestrial ecosystems on global, continental, and regional scales, due to the valuable land-surface property information that NDVI encapsulates.

$$\boldsymbol{NVDI} = \frac{\boldsymbol{NIR_{reflectance}} - \boldsymbol{Red_{reflectance}}}{\boldsymbol{NIR_{reflectance}} + \boldsymbol{Red_{reflectance}}}$$

Conceptually, NDVI is calculated through the normalized transformation of the ratio of near-infrared (NIR, around 850 nm) and red (650 nm) reflectance. It serves as an index of vegetation's absorptive and reflective attributes in these spectrums. Consequently, fluctuations in NDVI time-series denote variations in vegetation conditions proportional to the absorption of photosynthetically active radiation.

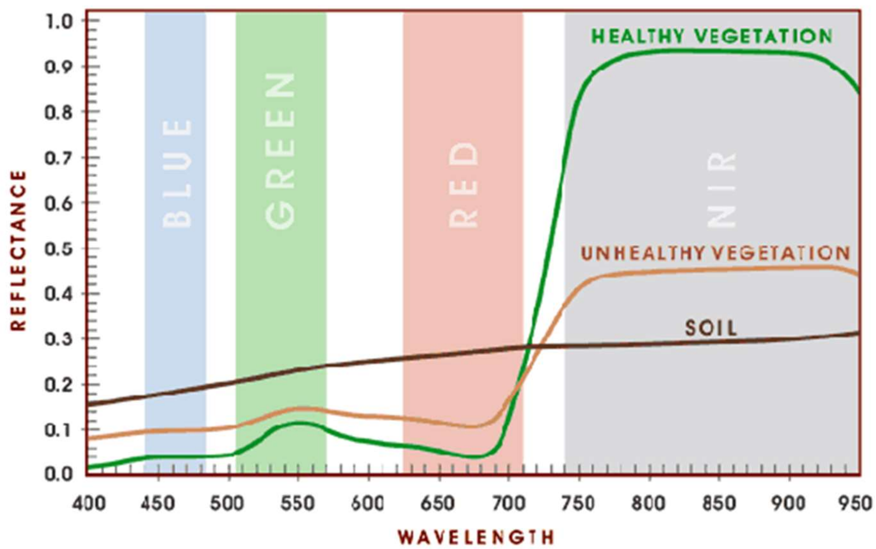

Figure 3 Contrasting Wavelength Responses of Healthy and Unhealthy Vegetation Compared to Soil Spectral Signature

In Figure 3, we present a comparative illustration showcasing the distinct wavelength responses of both healthy and unhealthy vegetation, juxtaposed against the spectral signature of soil. This visual representation serves to underscore the variations in spectral reflectance patterns exhibited by different elements within the agricultural landscape.

The upper segment of the figure demonstrates the wavelength response of healthy vegetation, characterized by distinctive peaks and troughs across the electromagnetic spectrum. These discernible features in the reflectance pattern correspond to specific physiological attributes of thriving plants.

In contrast, the lower segment illustrates the wavelength response of unhealthy vegetation. Here, deviations in the spectral signature become evident due to factors such as stress, disease, or nutrient deficiencies. This altered reflectance pattern provides insights into the compromised health of vegetation.

Adjacent to the vegetation responses, the figure showcases the spectral signature of soil. This baseline reference allows for the differentiation of vegetation-related spectral variations from those attributed to soil characteristics.

Notably, NDVI maps have received significant attention for delineating homogenous management zones for targeted nitrogen (N) fertilizer application. NDVI accurately reflects the state of plants at the moment of image capture. Hence, establishing NDVI-based homogeneous zones offers a swift and efficient way to gauge the immediate nitrogen requirements of plants before applying fertilizer. This is primarily due to NDVI's focus on live green vegetation, indirectly providing insights into nitrogen vegetation status. However, it's important to exercise caution when interpreting low green vegetation levels that result from factors other than nitrogen nutritional needs, such as pest infestations, diseases, or salt stress. In such cases, prescription fertilization maps based on NDVI might lose their utility. Defining precise N fertilization prescriptions is closely tied to the specific site and crop, underscoring the necessity of site-specific monitoring to corroborate information obtained from proximal or remote surveys.

1.4.7. Variable Rate Application (VRA)

Numerous potential benefits have been documented through diverse combinations of variable application rate practices[18].

Variable Rate Application (VRA) constitutes a technique that involves the strategic application of diverse input rates within distinct homogeneous zones across a field. The primary objectives of VRA encompass the optimization of profit, enhancement of input application efficiency, and the promotion of sustainability and environmental well-being (Grisso, 2011).

Precision farming places a significant emphasis on the capability to modify application rates and execute precise input distribution in alignment with the specific demands of crops. The scope of variable rate application extends to various inputs, including but not limited to plant growth regulators, defoliants, pesticides, water, and nitrogen applications. By tailoring input rates to correspond with the unique characteristics of different zones, VRA aims to foster improved resource utilization and better align agricultural practices with economic and ecological considerations.

1.4.8. Application Control in Precision Agriculture

An integral facet of precision agriculture lies in the nuanced control over diverse inputs, characterized by variable rates, distinct soil depths, and site-specific application within fields. This comprehensive loop of precision agriculture finds its culmination in the domain of application control. Precision agriculture necessitates the implementation of sophisticated control systems to modulate the dispersion of granular fertilizers, pesticides, and other inputs while accommodating the diverse needs of changing crop varieties, anhydrous nitrogen application, sprayers, irrigation, manure dispersal, and various tillage tools. The existing technology landscape already encompasses an array of solutions, each offering different levels of precision in input application (Anderson and Humburg, 1997; ASAE, 1991; Robert et al., 1993, 1995, 1996).

Precision agriculture places an overarching emphasis on the precision of every facet of application equipment. However, it is important to recognize that not all accuracy challenges are exclusive to precision agriculture. Variables such as driving precision, uniformity of distribution, field terrain, surface conditions, wind dynamics, and metering effectiveness collectively contribute to the variability encountered in input application across various agricultural contexts. Yet, certain aspects of application precision, specific to precision agriculture, warrant distinct consideration. These include transition times for rate or product adjustments, location-based precision control, and those dimensions of application where changes in rates or products directly impact the performance variability unique to precision agriculture practices.

By addressing the intricate dynamics of application control, precision agriculture strives to enhance the predictability, efficiency, and efficacy of input dispersion, ultimately fostering optimized crop growth and resource utilization.

1.4.9. Onion

The onion (*Allium cepa* L.), a biennial bulb crop belonging to the *Amaryllidaceae* family, is renowned and extensively cultivated as a vegetable crop. Its root system consists of numerous fasciculata and surface roots, primarily developing within the upper 20–25 cm of soil. The bulb, which is the consumable portion and exhibits varying shapes, originates from the enlargement of the basal part of leaves arranged in a central cauline axis[19].

The development and productivity of cultivated plants are primarily shaped by a combination of genetic attributes and the strategies employed in their management[20].

The initial factor encompasses diverse breeding methodologies aimed at enhancing crop variations, whereas the subsequent factor encompasses aspects such as planting schedules, spacing, fertilization methodologies, irrigation practice[Error! Bookmark not defined.].

Furthermore, the productivity can also be influenced by factors like climate conditions, soil type, and soil fertility[21]. Among the essential nutrients, nitrogen (N) plays a pivotal role, constituting approximately 80% of the total mineral nutrients taken up by plants. It is indispensable for essential processes like photosynthesis, as well as various physiological and biochemical reactions within plant metabolism. These include the formation of proteins, enzymes, amino acids, amides, nucleic acids, and plant hormones[22].

The correct and effective utilization of nitrogen is crucial for ensuring the overall sustainability of cultivation systems and the successful utilization of this essential nutrient[23]. Given their shallow and unbranched root system, onions are more vulnerable to nutrient deficiencies compared to the majority of other crops[24]. Consequently, onions require and exhibit positive responses to the application of fertilizers, particularly those rich in nitrogen. Effective management of nitrogen fertilizers in onion cultivation can enhance their quality, notably in terms of bulb size and shelf life, resulting in favorable economic outcomes for agricultural enterprises[25].

Simultaneously, effective management of nitrogen inputs serves to mitigate the adverse repercussions of nitrogen leaching in the form of nitrates, which can pose significant environmental threats. This concern is particularly pronounced in highly specialized regions where onions are commonly cultivated on sandy soils, characterized by limited nutrient retention and high permeability. Often situated in proximity to riparian or coastal areas, these regions face a substantial risk of groundwater quality degradation and surface-water eutrophication due to leaching. Attaining sustainable onion fertilization involves selecting appropriate formulations, precise application timings, and requisite doses tailored to the crop's needs. This approach aims to bolster productivity while adhering to nutrient requirements essential for optimal yield, thereby minimizing economic losses and curbing nutrient dispersion in the environment[26].

The application of remote sensing (RS) techniques in onion cultivation offers the potential to enhance various field operations such as growth monitoring and targeted fertilization, despite being nowadays very limited this approach in open field conditions (Messina et al., 2021)[27]. This approach also aligns with the implementation of precision agriculture strategies.

The cultivation of onions is a widely practiced agricultural technique in Italy, spanning over 12,000 hectares across the nation and yielding approximately 450,000 tonnes annually. This positions Italy as a significant player in the European onion market, alongside countries like The Netherlands and Spain. The regions with the highest onion cultivation concentrations are Emilia-Romagna (with around 3,000 hectares) and Veneto (with about 2,000 hectares), collectively accounting for over half of the national onion-growing area (ISTAT, 2018). Despite onions having a lesser quantitative production compared to other horticultural crops, the presence of high-quality local cultivars, such as Tropea and Borettana, makes onion cultivation an economically attractive choice for many farmers.

To mitigate undesirable effects like bolting, triggered by early spring low temperatures, selecting the appropriate onion cultivar according to local climatic conditions is essential. The climate also has a direct impact on onion bulb quality (Shigyo & Kik, 2008). Nitrogen stands as a vital component within crop production systems. Excessive nitrogen consumption can lead to a decline in nitrogen use efficiency (Raun and Johnson, 1999). Enhancing NUE (Nitrogen Use Efficiency) in crops, including onions, through modifications in agricultural practices, contributes to improved fertilizer efficacy, crop productivity, and overall sustainability of onion production systems.

In the Veneto region of northeastern Italy, efforts have been undertaken in recent decades to enhance the efficiency of the agricultural system and elevate agroecosystem quality. Nonetheless, further work remains, highlighted by recent modeling assessments of NUE for major crops in Veneto, with a median value of around 0.5 (Figure 5).

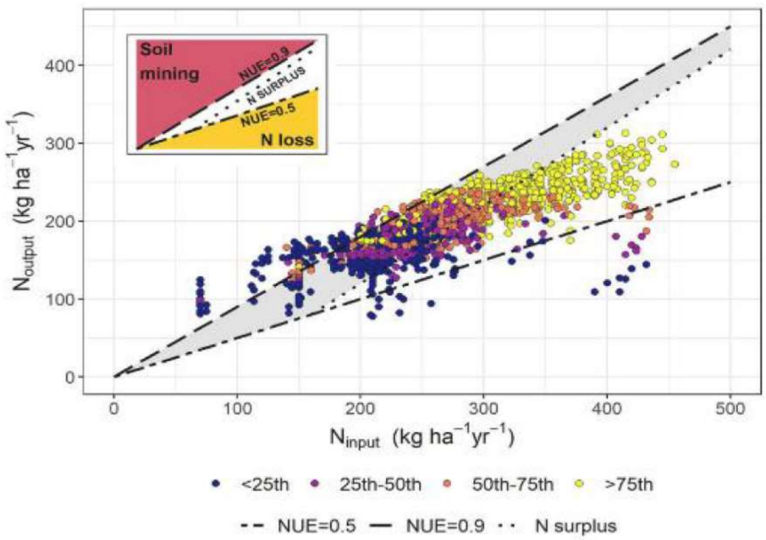

Figure 4 A graph representing the nutrient and N output from the main crops cultivated in the Veneto region. Source Longo et al., 2021.

To optimize total output and bulb size, substantial doses of nitrogen fertilizer are commonly applied without considering field variability. However, Precision Agriculture and Variable Rate Application (VRA) technologies are now ripe for implementation in horticultural crops like onions, as evidenced by previous studies conducted in southern Italy by Messina et al. (2020, 2021).

The escalating production costs have also impacted the entire Italian vegetable production sector, diminishing overall production competitiveness. Particularly, harvesting operations, if done manually, incur labor costs accounting for over 50% of total production costs (Abenavoli, 2004). Moreover, recent increases in fertilizer expenses are prompting farmers to explore alternatives and new technologies that can enhance profitability by reducing costs and maximizing fertilizer usage while maintaining high yield standards, as depicted in Figure 6 (Stone, 2000).

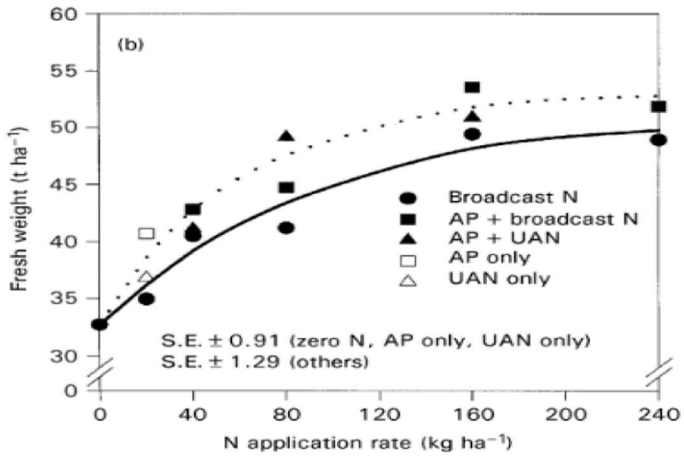

Figure 5 Graph representing the N application rate and yield response in an onion field experiment. Source Stone, 2000.

2. Aim of the Thesis:

The primary goal of this thesis is to conduct a comprehensive comparative analysis focusing on fixed and variable rate nitrogen applications in open-field Borettana onion cultivation within the municipality of Oppeano (Verona province), northern Italy. By harnessing advanced proximal sensing techniques, imagery data, and cutting-edge technologies such as NDVI imageries from unmanned aerial vehicles (UAVs), this study seeks to evaluate the feasibility of applying variable rate technologies (VRA) in onion fields. The aim is to determine the optimal nitrogen application strategy that can simultaneously enhance crop productivity while ensuring the judicious use of resources and minimizing the environmental impact.

After two years of field experiments where field and laboratory data were compared with UAV NDVI imageries –the thesis is part of a research project that involves DAFNAE-University of Padova, Orti dei Berici soc. coop, and Archetipo Srl– this work of thesis has taken advantage e of such experience by developing and testing specific algorithms for VRA techniques during the third year of experimentation, and also by evaluating the crop response to different fertilization strategies with field analysis and UAV imageries.

2.1. Specific Objectives:

1. Soil response to different fertilization strategies, through systematic collection of soil samples from the onion cultivated field. These soil samples will serve as the fundamental basis for accurate nitrogen content assessments, laying the groundwork for subsequent analyses.

2. Implementation of Nitrogen Application Strategies: This objective entails the practical application of both fixed and variable rate nitrogen strategies within strategically selected field points. The fixed-rate application will serve as a reference point, while the variable-rate application will consider the spatial variations in soil and crop conditions.

3. Utilization of Remote Sensing and NDVI Analysis: By harnessing state-of-the-art remote sensing techniques, including the computation of the Normalized Difference Vegetation Index (NDVI) using imagery acquired from unmanned aerial vehicles (UAVs), this objective aims to quantify the vegetation response to different nitrogen levels.

4. Spatial Analysis Through GIS: Geographic Information Systems (GIS) will be instrumental in processing the NDVI data, generating spatially explicit maps that vividly illustrate the distribution of vegetation health and nitrogen-related attributes across the onion cultivation area.

5. Identification of Data Relationships: This objective focuses on deciphering intricate relationships between proximal sensing data, particularly NDVI measurements, and the prevailing crop conditions. This analysis will be pivotal in comprehending the impacts of distinct nitrogen application approaches on the growth and productivity of Borettana onions.

6. Assessment of crop growth and productivity: An essential goal of this research is to assess the efficiency of onion crops in response to site-specific nitrogen applications. By meticulously evaluating the correlation between applied nitrogen levels and resultant crop yields, this objective aims to pinpoint the most effective nitrogen application strategy.

7. Holistic Technological Integration: Central to this study is the integration of diverse technological facets. Ranging from laboratory-based soil and vegetation analysis to advanced UAV-based remote sensing, the research showcases a comprehensive approach to agricultural investigation.

3. Materials and Methods

3.1. Study Area

The experimental site was located within the municipality of Oppeano (Verona province) in the northeastern region of Italy, approximately 90km from Padova. The study was conducted in a 25-hectare onion field cultivated with Borettana onions by Orti dei Berici Soc. Coop. Agricola. Borettana onions, an Italian onion variety, which hold significant economic and rural significance in this area.

The soil characteristics of the study site were identified using the pedology map of the Veneto region (accessible at https://gaia.arpa.veneto.it/). The soil in this region was classified as Arenosol, originating from a historically low calcaric plain. The depositional pattern exhibited sandy ridges interspersed with alluvial plains containing fine deposits dating back to the last glaciation.

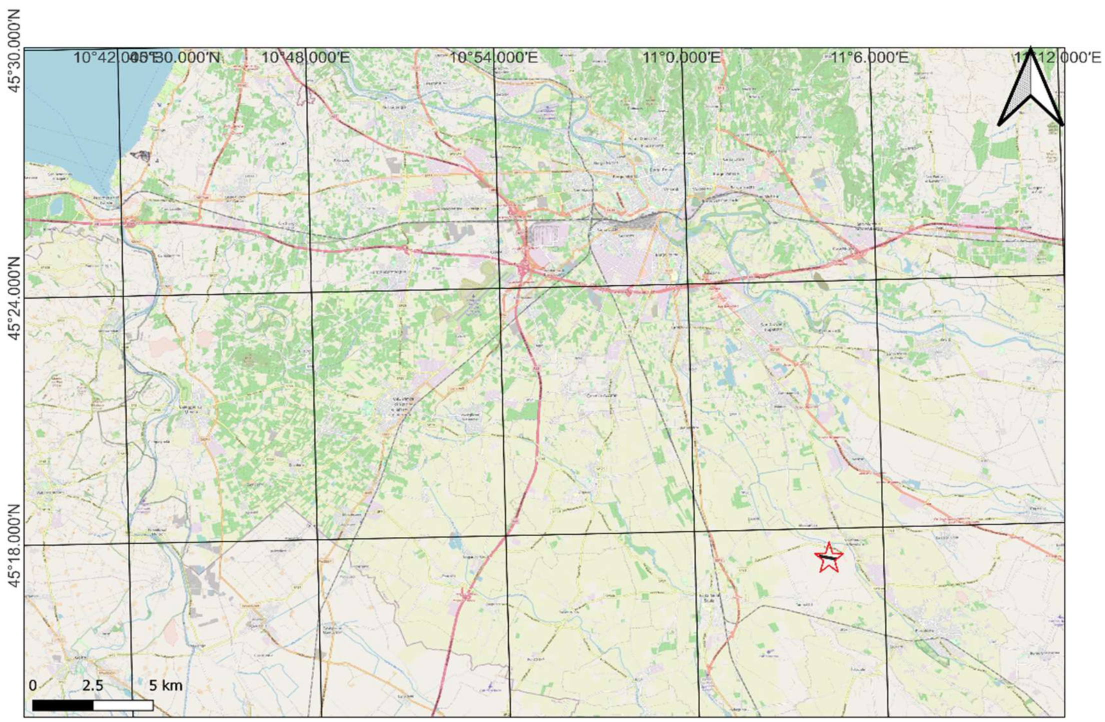

Figure 6 Experimental field located in municipality of Oppeano (Verona province).

The experimental trial was carried out on a designated area measuring 7.1 hectares, which constitutes a subsection of the total field. Within this area, individual plots measuring 48×74 square meters were established. The experimental design followed a completely randomized block design with five replications, each including two sub-replications for soil and vegetation analysis. The study included four distinct levels of total nitrogen (N) application in the form of sulfate ammonium (21% N), outlined as follows:

Table 1 Doses of ammonium sulfate are distributed according to treatments in comparison.

Treatments	**Fractional dose of $(NH_4)_2SO_4$ during the crop season**	**Total distribution (kg ha^{-1})**
N140	140 + 140 + 190 + 190 + 190 (+200)	1050 (fixed)
N90	90 + 90 + 140 + 140 + 140 (+200)	800 (fixed)
VRA-A	140 + 5 variable doses	variable
VRA-B	90 + 5 variable doses	variable

The VRA-A and VRA-B followed variable input doses based on the vegetation status and provided N requirements, including growth forecasts before next fertilization event. The only difference between “A” and “B” stems on the high and low dose input during the first fertilization event. A view of the field is provided in the map here below:

Figure 7 The experimental site: The sampling points are highlighted, i.e., two sub-replicates for each plot subject to treatment. The numbers identify the treatment being compared for each plot, with increasing numbers indicating the increasing dose of fertilizer.

The Borettana onion seeds were sown on February 12th, 2023. Subsequent to the sowing, a series of field visits were conducted on a regular basis to gather both vegetation and soil data, as well as to carry out

UAV surveys. The culmination of these efforts was marked by the harvest, which took place on July 20th, 2023. The initial field visit transpired on March 21st, 2023, with the primary objective of collecting soil samples. A comprehensive overview of the field operations, cumulative precipitation, and soil moisture conditions is succinctly presented in the graph depicted below:

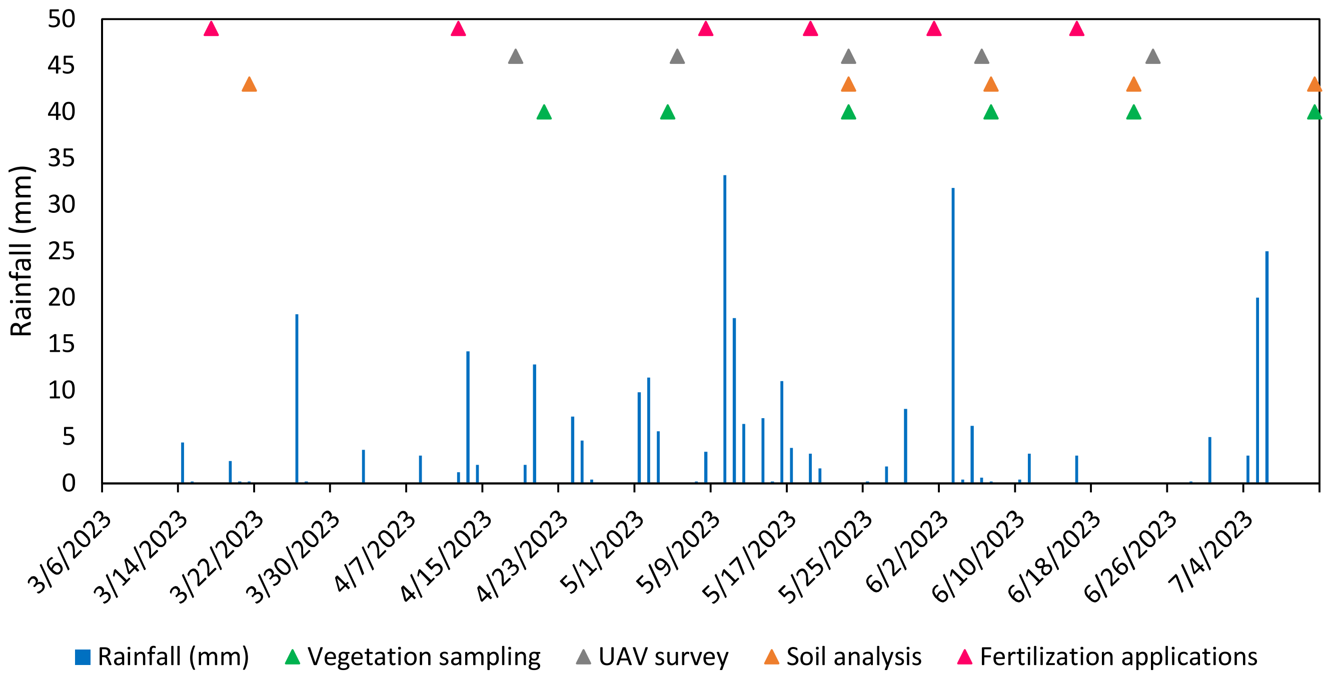

Figure 8 A summary of field operations and main weather conditions is provided in the graph below.

3.2. Nitrogen Application Strategies

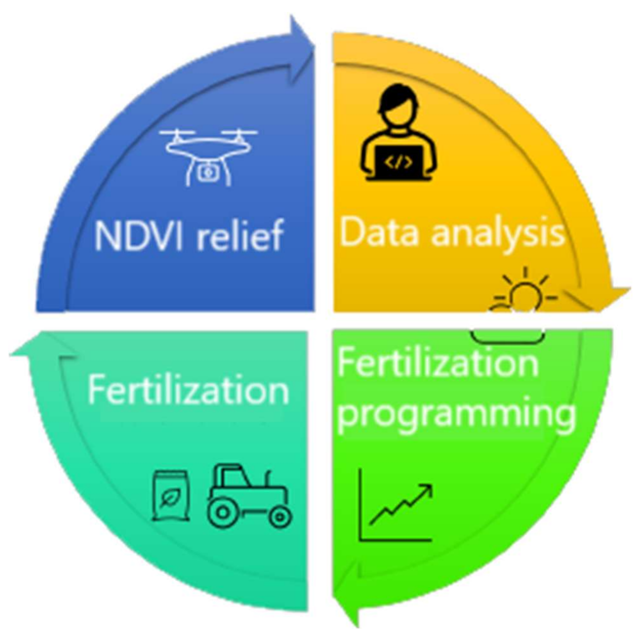

Figure 9 Conceptual scheme of the methodological approach for variable rate N application.

Two distinct nitrogen application strategies were employed for the study: fixed rate and variable rate. The fixed rate strategy involved applying a predetermined amount of nitrogen uniformly across selected sampling points. This strategy served as the baseline for comparison. The variable rate strategy utilized spatial information and collected data to determine optimal nitrogen application levels for individual sampling points, accounting for varying crop and soil conditions. The approach adopted in this study is the utilization of tailored algorithms, validated in the previous two years of experimentation, for N application rate in Borettana onion based on the crop growth status, the N requirement to reach the optimum N level in vegetation, and the provision of N to compensate for the forecast vegetation growth and N requirement until the following fertilization event. It means that remote sensing surveys must be integrated with spatial data analysis and weather forecasts to provide N prescription maps to the farmer (Figure 7).

3.2.1 Estimates of crop growth status

The estimate of actual crop growth is pivotal to determine the optimal N content that should be in total onion biomass. The approach adopted in this study to estimate total onion biomass (both belowground and aboveground) is based on past field surveys under similar pedoclimatic conditions and according to a management that is characterized by irrigation conditions (no water stress) and farmer monitoring about the status of vegetation in terms of pests and diseases control.

In particular, it was found a good relationship between growing degree days (GDD) and total onion biomass all along the cropping season as reported here below and as suggested by some other authors (Tesfay et al., 2011).

The GDD approach for onion cultivation involves the following steps:

1. Base temperature calculation: A base temperature (T_0) is established, typically around 6°C, below which crop growth is assumed negligible.

2. Temperature data collection: daily average temperature data (T_{Mean}) is collected from a weather station located near a meteorological station (in this case Salizzole; data provided by ARPAV, www.arpa.veneto.it).

3. Accumulation of GDD: GDD for each day are calculated as the difference between the average daily temperature and the base temperature as the season progresses. These GDD values, representing cumulative heat units, were computed considering a base temperature threshold (Eq. 1).

$$GDD = \sum_1^n (T_{Mean} - T_0) \qquad [1]$$

The relationship that was found between GDD and dry biomass (t/ha) is as reported in the figure below (Figure 10) and summarized by the following equation (Eq.2)

$$TotBiomass = 3 \times 10^{-7} \times GDD^{2.5402} \quad [2]$$

Where Tot Biomass is reported in t/ha is as reported in the figure below (Figure 10).

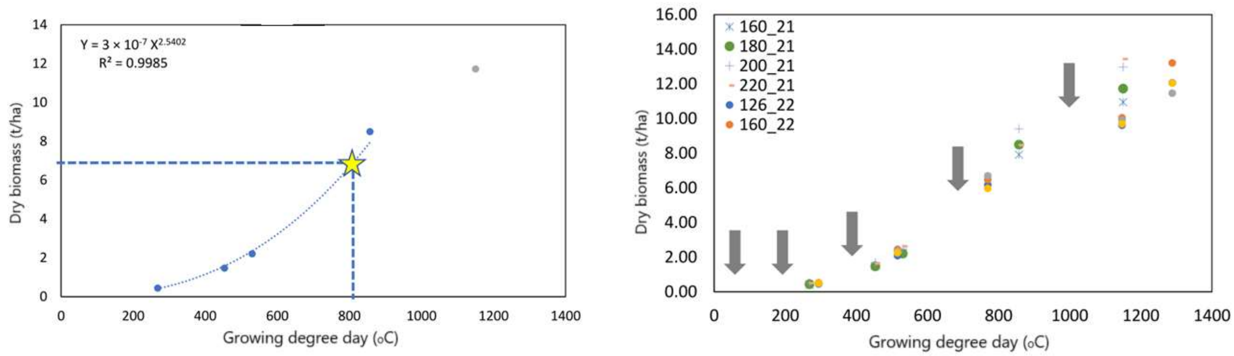

Figure 10 relation between GDD and dry biomass

3.2.2. Optimal N content in Vegetation

In this study, we employed the concept of Growing Degree Days (GDD) to estimate the total biomass of the onion crop. GDD was calculated using a specific equation tailored to our research needs. This approach allowed us to estimate the total biomass of the crop, providing valuable insights into its growth and development throughout various stages.

The estimation of optimal nitrogen (N) content in vegetation represents a pivotal component of our precision agriculture approach, particularly for variable rate nitrogen application. This estimation is achieved through the utilization of a dilution curve, which serves as a fundamental tool for determining the ideal N content that should be present within the crop biomass. The process involves a comprehensive understanding of the relationship between crop growth and N accumulation.

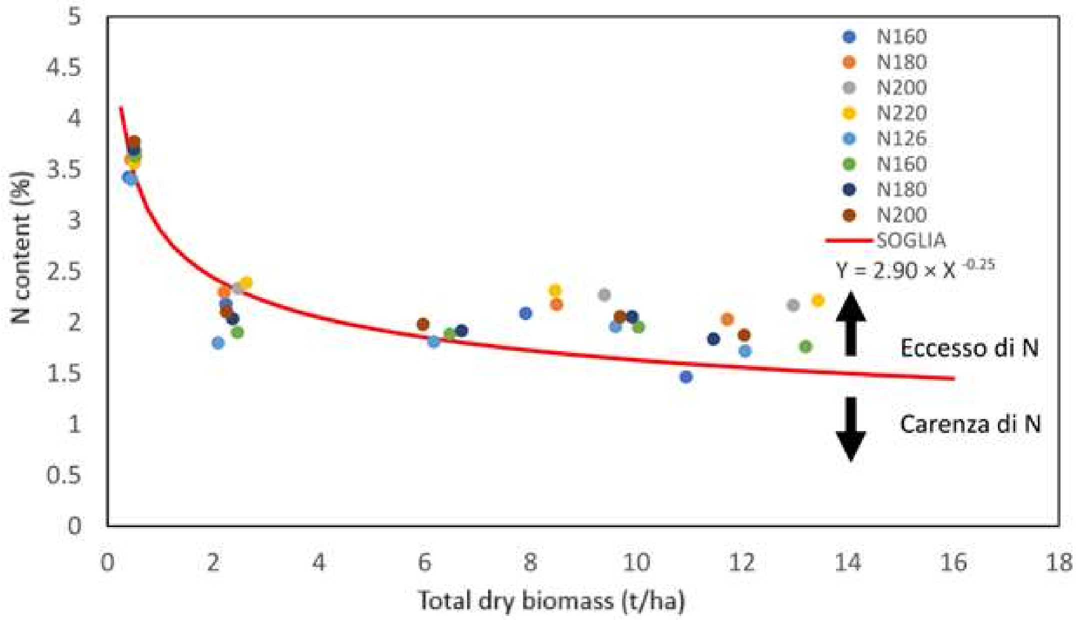

Figure 11 Dilution Curve for Optimal N Content

The dilution curve, as illustrated in Figure 11, show the relationship between crop growth during the growing season, typically measured in terms of dry biomass, and the corresponding N content within the total vegetation tissues (aboveground plus belowground). The curve helps in identifying the critical thresholds at various growth stages, indicating the ideal N concentration required for optimal crop development. By using this dilution curve, we can precisely gauge the N needs of the crop as it progresses through different growth phases.

The equation representing this dilution curve is as follows:

$$N\ content\ \% = 2.9 \times ((TotBiomass)^{-0.25})) \qquad [3]$$

This equation serves as the foundation for estimating the optimal N content that should ideally be present in the biomass at any given growth stage. It enables us to establish a baseline for N requirements (Eq. 4), which can then be compared to the actual N content obtained through our remote sensing and GDD-based methodologies.

$$N_{opt} = \frac{Percentage\ of\ N\ content \times TotBiomass}{100 \times 1000} \qquad [4]$$

where N_{opt} is the optimal N content (kg ha^{-1}) in each growing stage in total onion biomass. The delta or the difference between the optimal and actual N content forms the basis for precise variable rate nitrogen application strategies.

3.2.3. Actual onion N content

The actual N in the total vegetation, both considering the aboveground and belowground biomass, was estimated by finding a relationship with remote sensing NDVI surveys that were conducted in the previous two years with the collaboration of Archetipo Srl that mapped some experimental fields nearby with UAV technology, and the field surveys that were simultaneously made for ground-truth vegetation sampling followed by laboratory N vegetation analysis.

The procedure is as follows:

1. NDVI data acquisition: NDVI values are acquired through multispectral imagery obtained from the drone UAV remote sensing system. This imagery captures the variation in vegetation reflectance, indicating plant health and, in this case, the N content (kg ha^{-1}).

2. Field survey: the N content in vegetation is calculated through ground-truth data meaning field samples collection and laboratory analysis on vegetation. These data include vegetation N content (kg ha^{-1}) at fine resolution (< 1 m).

3. Algorithm development: We developed a specialized algorithm to analyze our data. This algorithm involved interpolating the data points on an x-y graph. We utilized the solver tool in Excel to optimize the algorithm, minimizing the sum of squares to achieve the best fit. The resulting equation (5), along with the graph representing its relationship, is presented and explained in detail in the following section.

$$N_{real} = 20 + 320^{NDVI} \quad [5]$$

where N_{real} is the actual estimated nitrogen content (kg ha^{-1}) in total onion biomass and NDVI is the index calculated from multispectral UAV imagery.

We continued by systematically extracting nitrogen content in kg ha^{-1} for individual pixels within the Normalized Difference Vegetation Index (NDVI) map. This step was guided by an analytical formula derived from a graph depicting the relationship between NDVI and N kg ha^{-1}. This approach allowed us to determine N content for each pixel, resulting in the creation of a new raster map referred to as "N Observation."

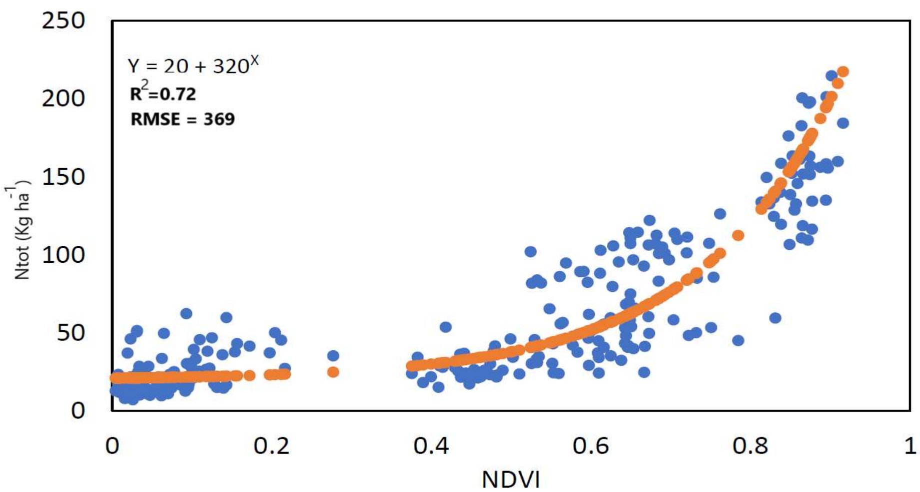

Figure 12 relation between NDVI and total nitrogen (kg ha^{-1})

3.2.4. Nitrogen fertilization prescription map and application

Based on the procedure explained above, it was finally possible to yield prescription maps about the exact N dose that should be provided to onion at a fine resolution. In this case the estimate was based on the evaluation of the difference between the optimal N content and the actual N content in vegetation that was previously described, to which it is added the estimated calculation of the N dose up to the subsequent fertilization intervention. This is estimated on the basis of the ordinary management of the field thanks to the information provided by the farmer, and on the basis of a meteorological forecast (7-15 days) and GDD which determine the expected increase in biomass. Integrating the results of the steps, the algorithm generates prescription maps that outline the precise N dose to be provided to the onion crop at a fine resolution. These maps highlight areas where N application should be adjusted based on the crop's specific needs. By employing this algorithm, we ensure that nitrogen fertilization is tailored to the unique growth dynamics of the onion crop, minimizing both underutilization and excessive use of nitrogen resources. This approach promotes sustainable and efficient agricultural practices, optimizing crop yield while minimizing environmental impact.

$$N_{Req} = (N_{opt-T0} - N_{real}) + N_{opt-T1} \quad [6]$$

Where the variable rate N application (NReq, kg ha^{-1}) is the delta between the optimal and then real in a given monitoring time T0 plus the optimal expected amount in vegetation just before the following fertilization event T1.

3.3. Acquisition of NDVI Data through UAV Proximal Sensing

The acquisition of NDVI data through UAV proximal sensing represents a pivotal aspect of this study. NDVI, an abbreviation for the Normalized Difference Vegetation Index, serves as a widely utilized metric for gauging the presence of live green vegetation within crops. The sensors employed in this process are strategically positioned above the crops and engage in the measurement of reflectance across various colors or light wavelengths. This reflective data is then harnessed to calculate the NDVI index, thereby offering critical insights into the state of vegetation health and vitality.

3.3.1. Instrumentation

The multispectral aerial acquisitions were meticulously executed using a specifically configured "DJI Matrice 600 Pro" drone. This hexacopter, falling within the category of class L (Light), boasts substantial dimensions and is engineered for versatility. With a maximum take-off weight (MOTOM) of 12 kg, this drone exhibits exceptional stability, even when confronted with wind speeds exceeding 15 km/h. This stability is attributed to the meticulous balancing of its engines and the optimization of propeller efficiency.

The UAV employed in this study is enriched with a sophisticated positioning system. This system is underpinned by a GPS receiver and an Inertial Measurement Unit (IMU), ensuring an impressive degree of flight stability, even during hoovering and in the presence of moderate winds. This stability translates into consistently steady video and image-capturing capabilities, a hallmark of the UAV's performance in this research endeavor.

Figure 13 The DJI Matrice 600 drone used in aerial monitoring activities.

The acquisition of multispectral aerial images was executed utilizing the advanced RedEdge MX MicaSense sensor. This sophisticated sensor exhibits the remarkable capability of concurrently capturing five distinct spectral bands, namely blue, green, red, near-infrared, and infrared. During the image acquisition process, an indispensable companion to the sensor was the Downwelling brightness sensor (DLS2), which seamlessly integrated with the setup. The DLS2 plays a pivotal role by facilitating the measurement of ambient light conditions throughout the flight. This integration serves the essential purpose of enhancing the accuracy and reliability of data collection, particularly in scenarios characterized by variable light conditions.

3.4 Monitoring of Soil and Vegetation Growth

3.4.1 Soil Sampling and Analyses

To establish a robust foundation for subsequent analyses, soil samples were meticulously gathered on March 21st, 2023, before any fertilizer application. A total of 40 points within the field were carefully selected for this purpose, and samples were extracted from the topsoil profile at a depth of 0-20cm. These samples underwent comprehensive analyses to assess their physical and chemical attributes.

The analysis of soil texture led to the classification of the soil as (insert soil classification). Furthermore, the examination of soil organic carbon (SOC) content consistently indicated levels below 0.6%. These findings collectively contribute to a nuanced understanding of the soil's characteristics and lay the groundwork for the subsequent stages of the study.

Table 2 Mean soil properties (± standard error) in the plots under monitoring.

	Sand (%)		Silt (%)		Clay (%)		SOC (%)		N-tot (%)		C/N	
N140	60.4	±0.5	20.2	±0.4	19.4	±0.2	0.79	±0.01	0.07	±0.00	11.32	±0.08
N90	61.5	±0.8	20.2	±0.5	18.2	±0.3	0.72	±0.01	0.06	±0.00	11.58	±0.10
N A	62.5	±0.3	19.9	±0.2	17.6	±0.1	0.76	±0.01	0.06	±0.00	11.96	±0.09
N B	62.7	±0.5	19.8	±0.3	17.6	±0.2	0.75	±0.01	0.06	±0.00	11.52	±0.12

Throughout the duration of the cropping season, the identical positions (as illustrated in Figure 5) served as the sampling sites for soil collection. Subsequently, soils were sampled three more times at the same depth for further analysis.

Upon collection, the soil samples were transported to the laboratory for subsequent procedures. To prepare them for analyses related to soil organic carbon (SOC) and texture, the samples were placed in aluminum foil containers and allowed to air dry under ambient room temperature conditions. Texture analysis was conducted on the soil samples that had been sieved at 2mm, while those designated for SOC analysis were sieved at 0.5mm.

In the case of soil samples intended for ammonium-N and nitrate-N analyses, a different protocol was adhered to. These samples were promptly frozen to prevent the degradation and transformation of nitrogen compounds until the time of analysis. This meticulous approach ensured the preservation of the sample integrity and the accuracy of subsequent nitrogen-related assessments.

3.4.2 Aboveground and belowground vegetation monitoring

Throughout the crop growing season, a systematic monitoring of both above-ground and below-ground vegetation was conducted. This involved sampling the biomass in a defined area of 0.25 x 0.25 m2 within all designated sampling plots. Additionally, essential parameters such as plant height (measured in centimeters) and plant density (number of plants) were recorded.

Figure 14 Samples of soils

Upon completion of the sampling process, the collected plant samples were stored in a refrigerator to prevent any potential moisture loss prior to the analysis of fresh biomass.

To determine the fresh biomass of the plant samples, the vegetation was carefully cleaned to remove any soil particles and residual water, while also accounting for the number of plants present in each sample. Subsequently, the fresh biomass was quantified. Following this, the vegetation samples were dried at a temperature of 65 °C until a constant weight was achieved, allowing for the accurate measurement of dry biomass.

The fresh and dry biomass calculations were performed separately for the above-ground and below-ground portions of the plants. To achieve this, the plant parts were meticulously separated using scissors. Each fresh sample was weighed and labeled with a unique identification (ID) for precise documentation.

For the dried samples, a weight measurement was taken before the samples were crushed into a powdered form, utilizing either a mortar and pestle or a mixer grinder. These powdered samples were then securely packed into small containers, specifically Eppendorf tubes, and sent to a laboratory for subsequent analysis to determine the total nitrogen content.

3.4.3 Data analysis and statistics

The data collected from various aspects of the study, including soil properties, sampling points, fertilization doses, timestamps, tissue characteristics (above and below ground), fresh and dry biomass, plant height, number of plants, bulb diameter, and more, were meticulously recorded in Microsoft Excel. These recorded data were then utilized for the creation of pivot tables, which were subsequently transformed into histograms and line graphs to visually represent the information.

To manage the georeferenced data, tools such as Google Earth and QGIS software were employed. These platforms facilitated the management of databases containing details about vegetation, soil properties, and NDVI based on the specific geographical locations of the sampling points. Thematic maps were generated using this information. Initially, a .kmz polygon file was converted into a shapefile using the Projected Coordinate System WHS84 / UTM 33N.

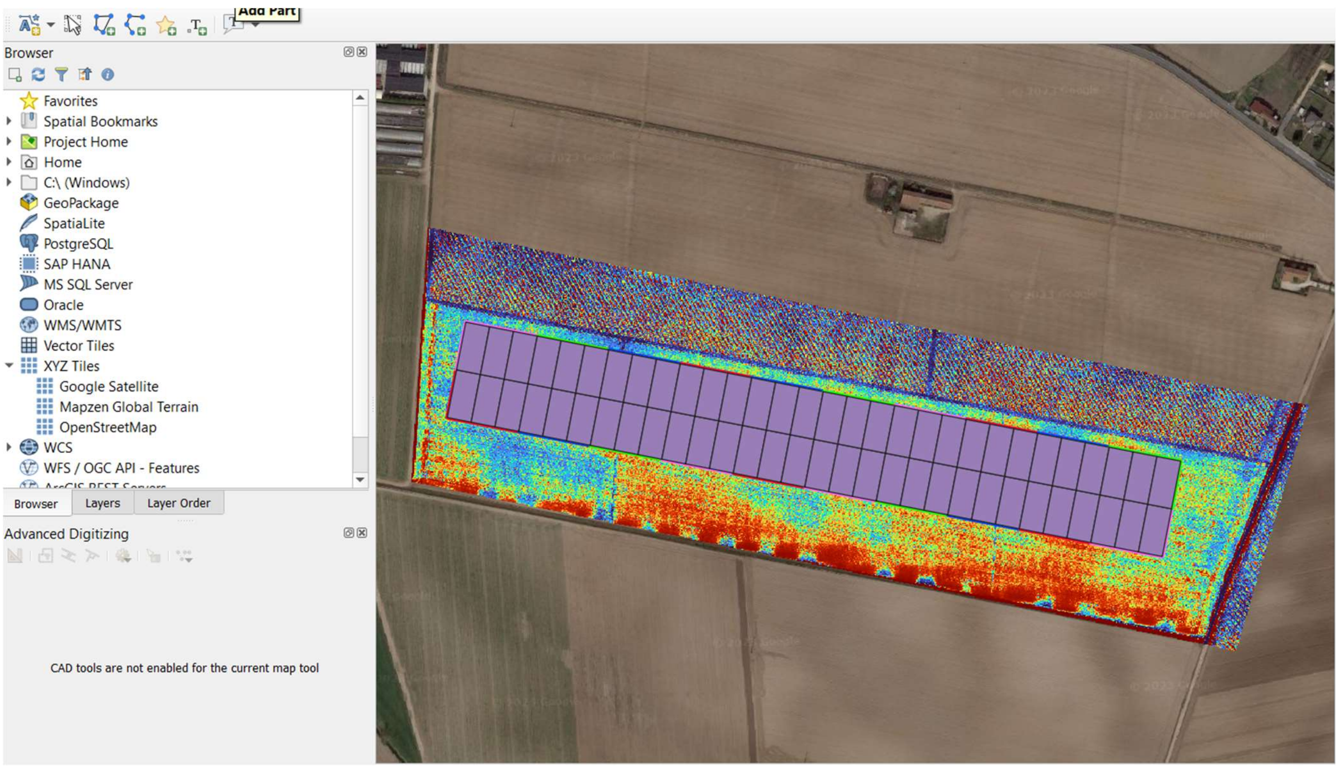

Figure 15 Convert map in QGIS.

The georeferenced sampling points within each plot were then identified and their identifiers were included in an attribute table. This table contained essential information such as IDs, fertilization rates, and more. Throughout the cropping season, data gathered from both field surveys and UAV imagery were integrated into this attribute table.

Statistical analyses were conducted to assess the presence of significant differences among the various treatments (fertilizations) concerning key parameters, including yield, N input, N uptake, and nitrogen use efficiency. These analyses aimed to provide a rigorous evaluation of treatment effects on these critical agricultural factors.

4. Results and discussions

4.1 Crop Growth Dynamics

In this section, we delve into the dynamics of crop growth, shedding light on the intricate processes that govern the development and progression of the Borettana onion plants throughout their cultivation cycle. By examining various facets of crop growth, including vegetative biomass accumulation, phenological stages, and physiological responses, we aim to provide a comprehensive understanding of the temporal evolution of the crop within the study area. The analysis of crop growth dynamics offers valuable insights into the interplay between environmental conditions, nutrient availability, and plant responses, thereby contributing to the broader context of precision agriculture strategies for onion cultivation.

4.2 NDVI mapping

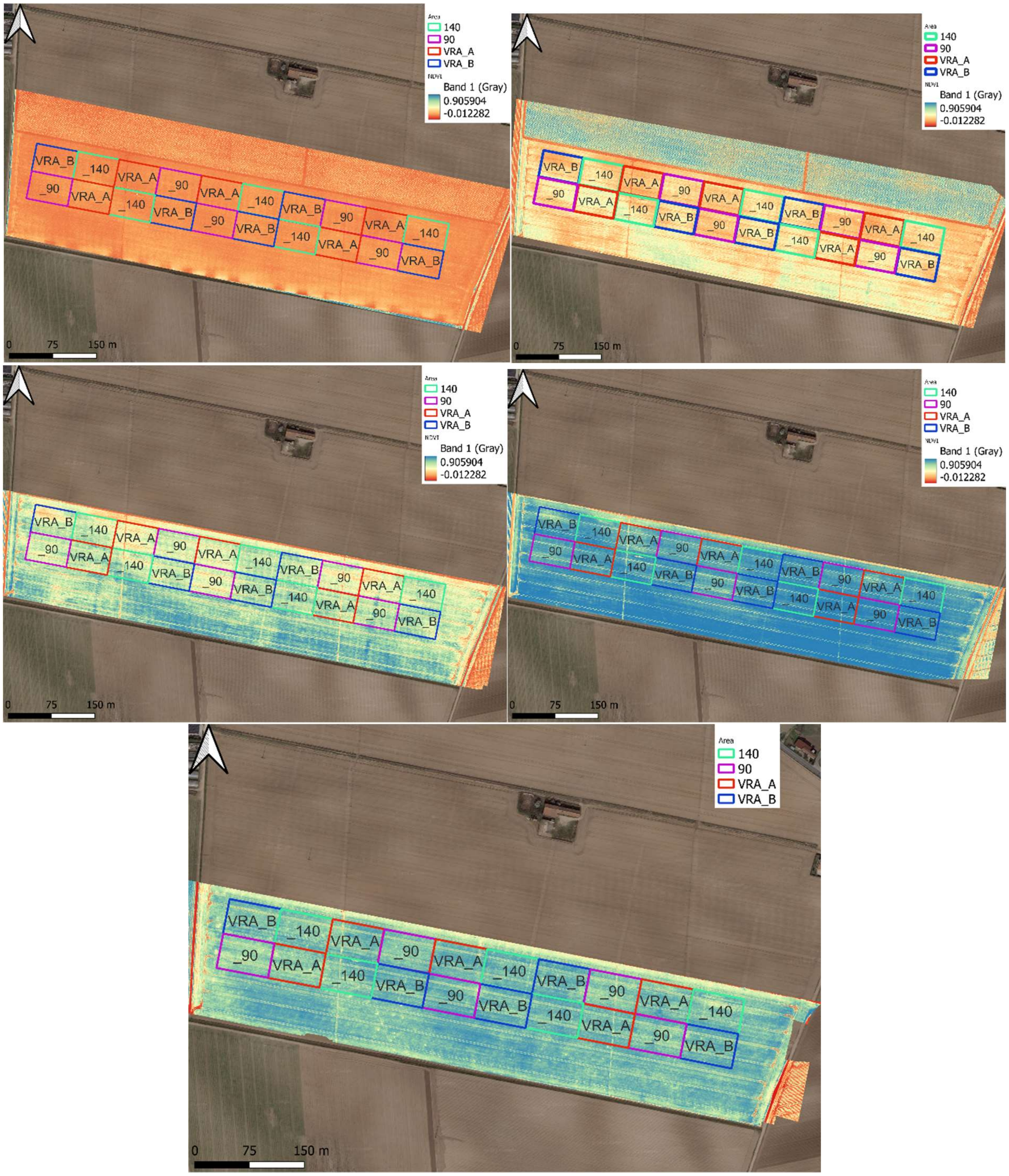

Figure 16 Maps of NDVI Raster during the cropping season: 18/04/2023, 05/05/2023, 23/05/2023, 06/06/2023, 24/06/2023.

The figures and maps presented in this study provide valuable insights into crop requirement estimation using UAV-based proximal sensing technology. The Normalized Difference Vegetation Index (NDVI) analysis (Figure 16) reveals the expected increase of NDVI through the growing season at different time points, from the first monitoring time (18/04) when vegetation was just a sprout, up to NDVI maxima at June 6 (> 0.80). After that vegetation started to desiccate and NDVI drop down to values ≤ 0.76 (Figure 17).

Figure 17 pictures during the cropping season: 21/03/2023, 21/04/2023, 04/05/2023, 23/05/2023, 07/06/2023, 11/07/2023.

Additionally, the biomass maps (Figure 18) generated from drone data revealed some spatial heterogeneity of vegetation across the field that was not dependent on fertilization rate, rather from soil variability. Some arbitrary colour-coded classification maps were also created (Figure 16), suggesting such NDVI differentiation. It is noteworthy that despite uniform fertilization treatments within specific plots, substantial heterogeneity in vegetation growth is evident. For instance, during T2, T3, T4, and T5, the "Fixed_value_90" treatment exhibited the lowest nitrogen absorption rate (27.6 kg ha^{-1}) and the highest absorption rate (>93.4 kg ha^{-1}), as depicted in Figure 22. Geographically, the southeastern region of the experimental field consistently exhibited lower onion yields (t/ha), irrespective of the fertilization treatment applied. These findings underscore the influence of various factors on crop growth and productivity, highlighting the potential benefits of precision agriculture in optimizing resource allocation.

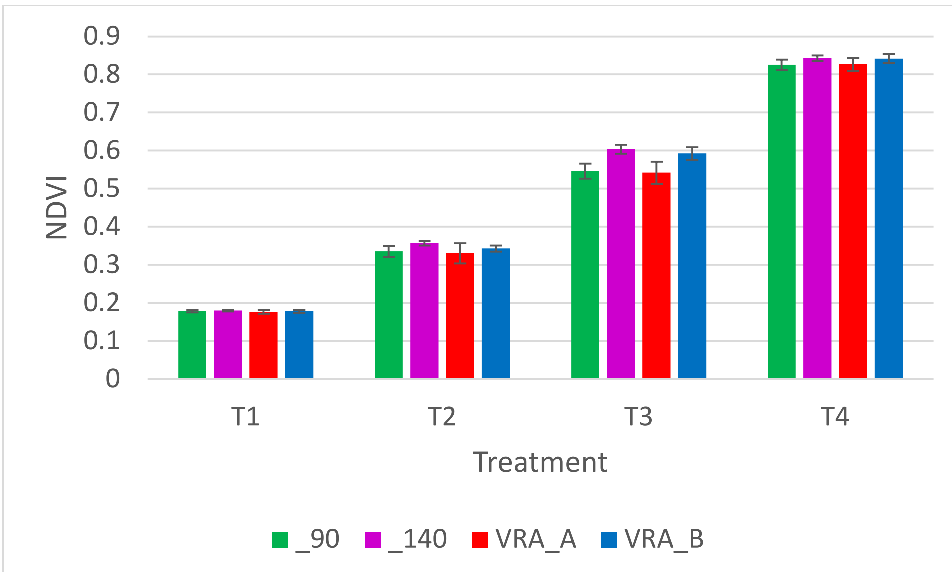

Figure 18 Mean NDVI for each treatment values during the cropping season.

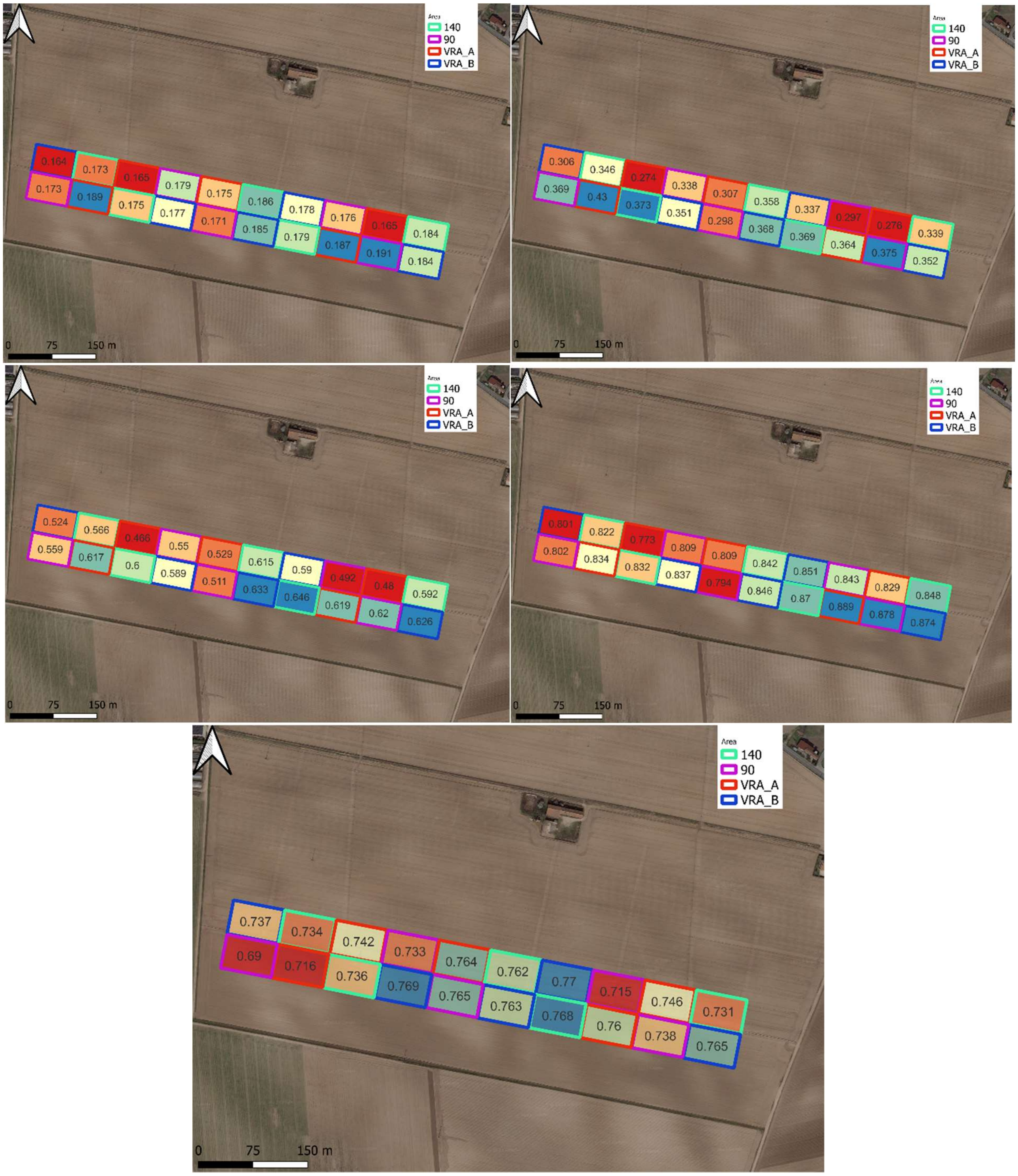

Figure 19 Maps of Mean NDVI values for each plot during the cropping season: 18/04/2023, 05/05/2023, 23/05/2023, 06/06/2023, 24/06/2023.

4.3 Nitrogen estimated from NDVI

Figure 23 visually illustrates the nitrogen content within the vegetation across different time intervals (T1, T2, T3 and T4). Notably, the period of T4 stands out as the phase when onion growth is most pronounced, marked by the development of green stems. Consequently, it's expected to observe a reduction in nitrogen content during T5, as the NDVI values during this phase are lower compared to the robust growth observed in T4. During T1, T2, and T3, the "Fixed_140" treatment demonstrates the highest nitrogen content. In contrast, during T4 and T5, the "VRA_B" treatment exhibits the highest nitrogen levels. These trends highlight the dynamic nature of nitrogen distribution in response to growth stages and treatment variations.

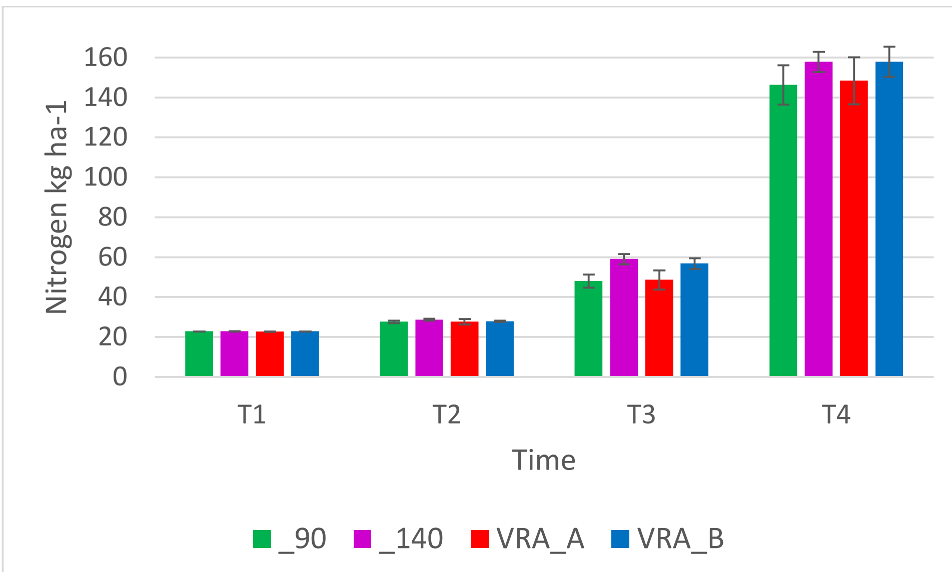

Figure 20 Nitrogen (kg ha^{-1}) values during the cropping season

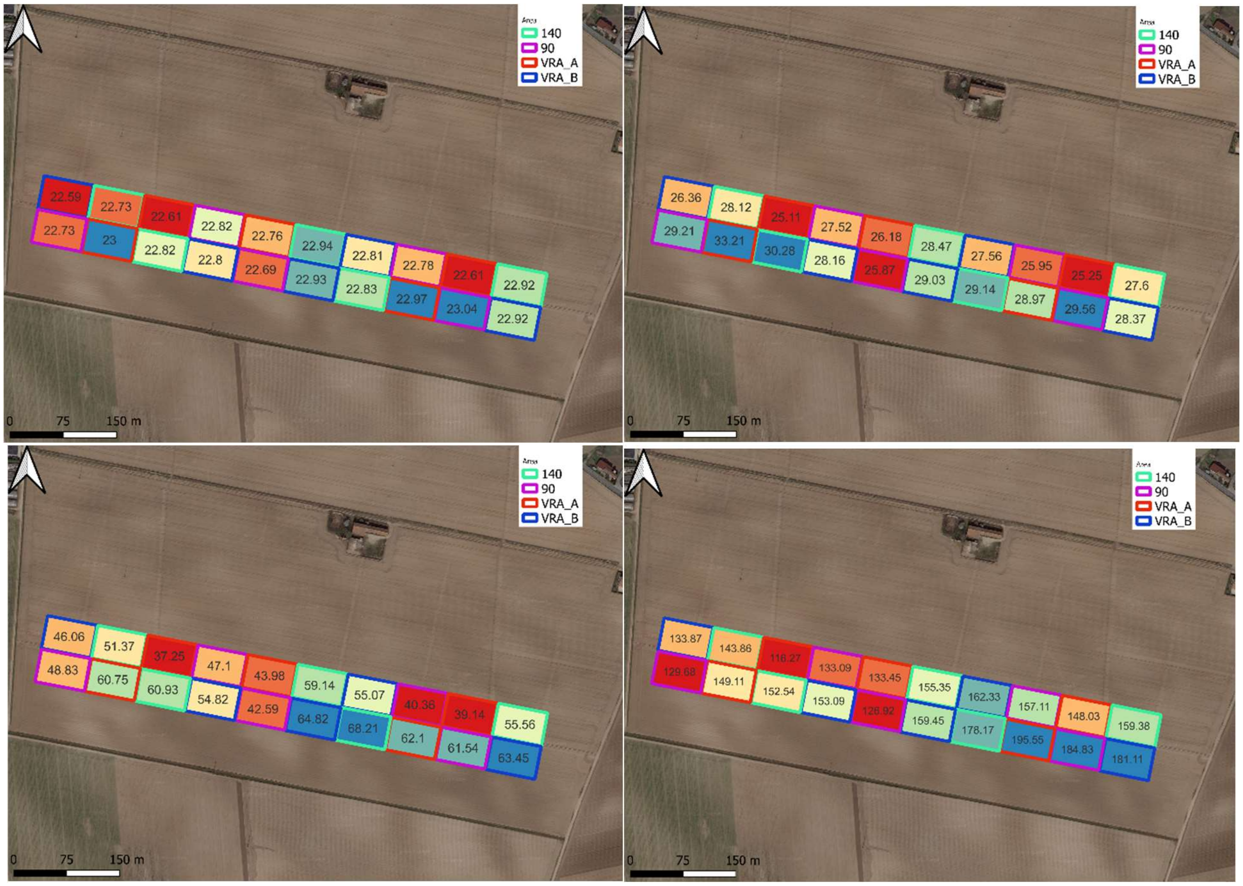

Figure 21 Maps of Nitrogen (kg ha^{-1}) values during the cropping season: 18/04/2023, 05/05/2023, 23/05/2023, 06/06/2023.

4.4 Nitrogen prescription

Figure number 25 portrays the predicted nitrogen requirements for each treatment during the various fertilizer application cycles, with assistance from NDVI maps. Evidently, the F5 period registers the Among the treatments, the plots associated with VRA_A exhibit the most substantial nitrogen requirements, aligning with the plant's natural growth requirements during this phase. It is noteworthy that VRA_A, being a variable rate application, had an average nitrogen dosage higher than the conventional fixed doses of 40 kg N ha^{-1} typically used by farmers. Conversely, treatment _90, which follows a fixed-rate application, displayed the lowest nitrogen demand. These variations in nitrogen requirements can be attributed to the specific vegetation and soil characteristics associated with each treatment during this particular growth phase.

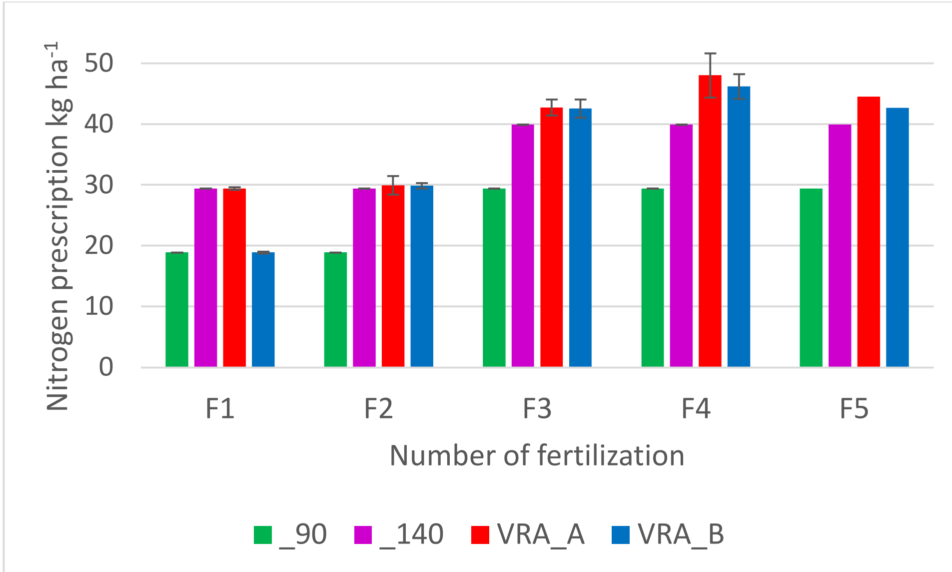

Figure 22 Nitrogen prescription (kg ha^{-1}) during the cropping season: 19/04/2023, 15/05/2023, 26/05/2023, 08/06/2023, 23/06/2023.

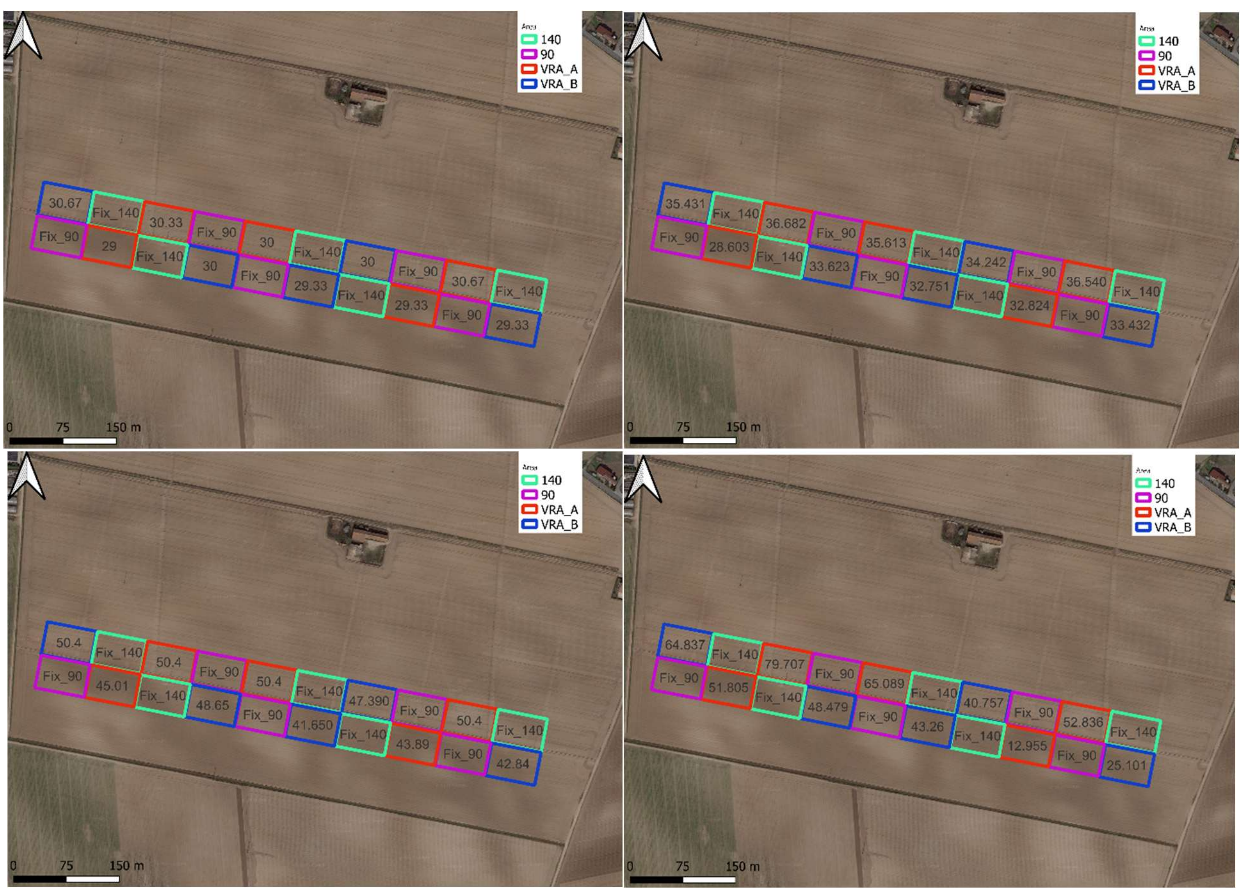

Figure 23 maps of Mean of Nitrogen prescription (kg ha^{-1}) during the cropping season: 15/05/2023, 26/05/2023, 08/06/2023, 23/06/2023.

4.5 Above ground fresh biomass

The graph depicted below illustrates the variations in fresh biomass over time for the leafy components of the crop. The fresh leaf biomass exhibited distinctions contingent on the different stages of crop growth and the application of varying nitrogen doses. Notably, the management of nitrogen fertilization exerted a discernible impact solely on aboveground biomass during the T4 sampling period (07/06/2023). Specifically, within the _140 treatment, augmenting the N dosage up to 29 kg ha^{-1} induced a consistent escalation in fresh above-ground biomass in contrast to the _90 and variable rate counterparts. In terms of fresh aboveground biomass, the treatment _90 registered the lowest values. As elucidated in Figure 15, subsequent to T4, there was a decline in fresh aboveground biomass, coinciding with the phase in which onion bulbs underwent growth, and the green foliage started transitioning to a yellowed and desiccated state (T5). Furthermore, during the T1 sampling period, the plants were in the seedling stage, resulting in an absence of significant fresh biomass within the field.

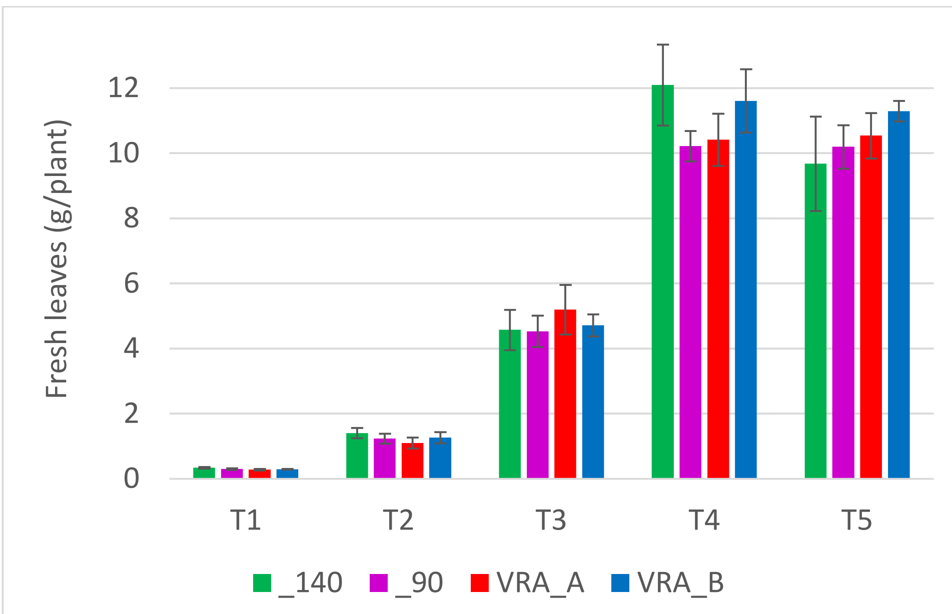

Figure 24 Above ground fresh biomass (g/plant).

4.6 Belowground fresh biomass

The distribution of fresh bulb biomass exhibited disparities in accordance with distinct temporal phases related with the growth season. Nevertheless, the application of nitrogen at varying doses did not yield discernible distinctions in this regard. It is worth noting that substantial alterations became evident during the time period denoted as T5 (22/06/2023). This notable shift is attributable to the cessation of growth in the upper section of the plant, coinciding with the commencement of growth in the lower section, which comprises the bulbs.

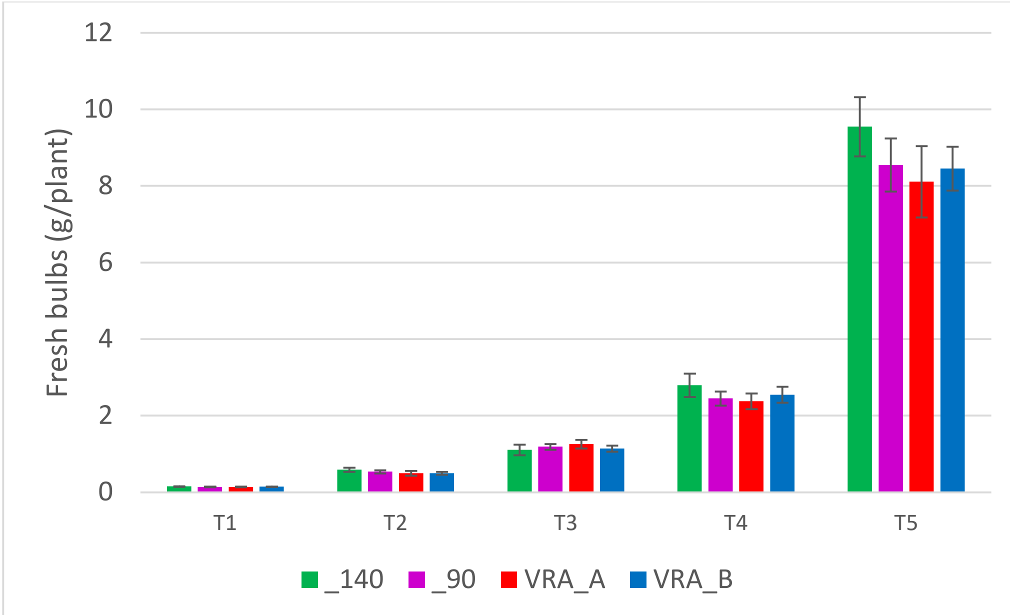

Figure 25 Below ground fresh biomass (g/plant).

4.7 Number of plants

Figure 26 presents the number of plants per square meter. The data in the graph are quite homogeneous between treatments and dates all through the experiment. To note that this variability on number of plants depends on the sowing density that can differ from one sampling area to the other. Anyway, the number of plants is in the common range of Borettana onion cultivation made by Orti dei Berici (Sangetaam, 2021).

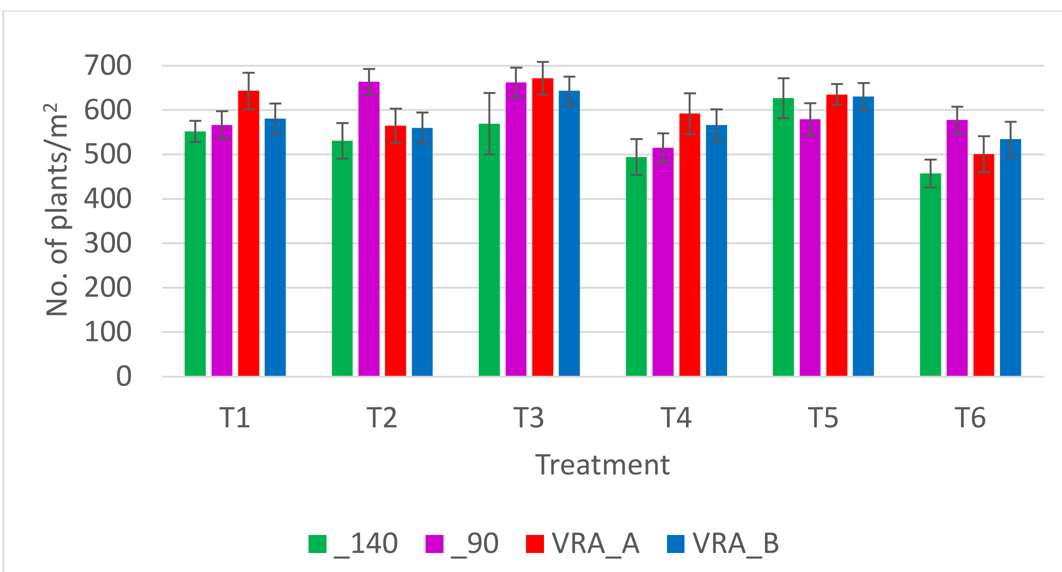

Figure 26 Number of plants/m2.

4.8 Average of dry yield at harvest

The graph below (Figure 27) illustrates the average dry yield at harvest, expressed as dry biomass in t ha^{-1}. No significant differences were observed among the various fertilization treatments, likely attributable to substantial variability within the sampling areas.

Observing Figure 27, a clear distinction emerges wherein the lowest harvest quantity is associated with treatment VRA_A, while the highest yield is attributed to treatment VRA_B. However, it is evident that this disparity in harvest quantity cannot be solely attributed to fertilization rates. To elaborate, despite treatment VRA_B receiving a higher nitrogen input compared to treatment _90 (with constant nitrogen application rates of 168 and 220.5 kg ha^{-1} for treatments _90 and _140 throughout the entire period, and 194.57 kg ha^{-1} and 180.18 kg ha-1 for treatments VRA_A and VRA_B, respectively), it yielded a higher crop output.

It's important to note that within VRA-A, there were sub-plots with notably low nitrogen inputs. The minimum nitrogen input in VRA-A was 29.4 kg ha^{-1}, and the yield in these sub-plots was 194.57 kh ha^{-1}. Nevertheless, a statistical examination reveals no significant divergence in harvested product quantity among the treatments.

To note, also, that the _140 treatment was not thought as the upper limit of N inputs provided by the farmers, suggesting that VRA can also suggest higher inputs whether required, but with a spatial variability approach. This discrepancy suggests the presence of other influencing factors, potentially relating to differences in soil type and vegetation characteristics.

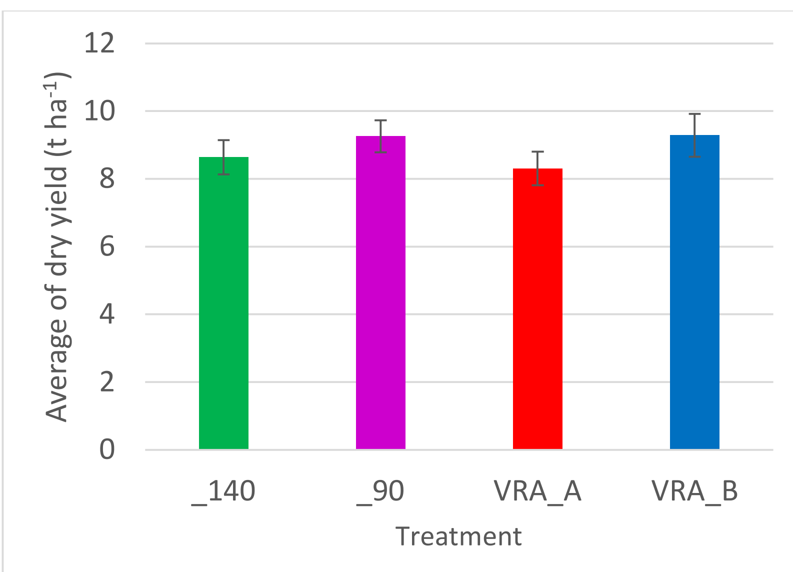

Figure 27 Average of dry yield (t ha^{-1}).

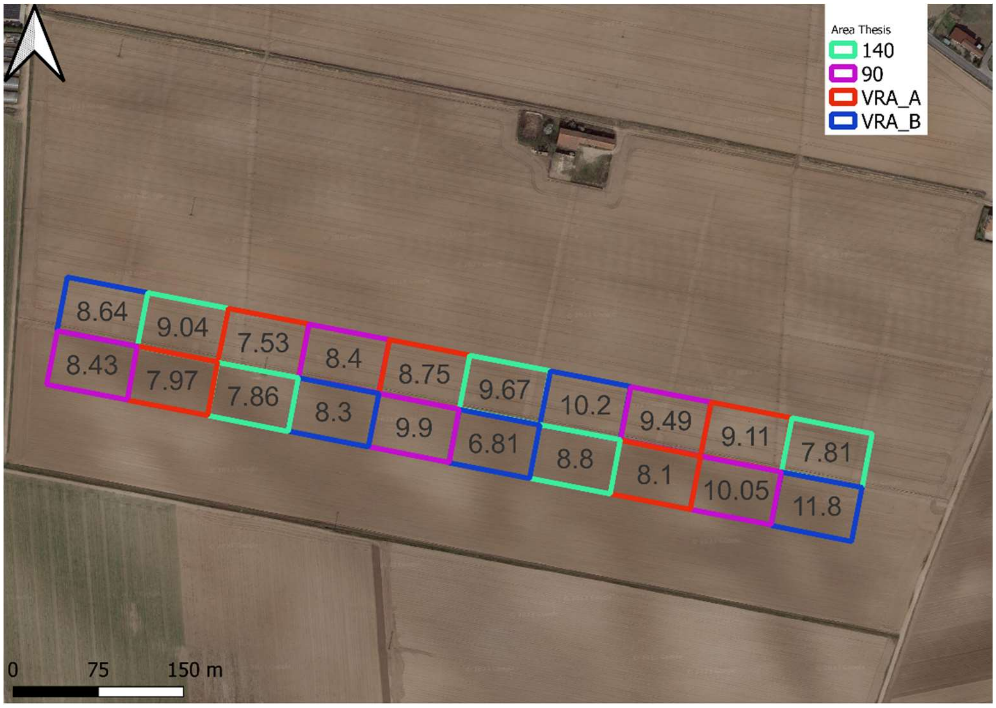

Figure 28 Map of dry yield (t ha^{-1}) in the different tested plots.

4.9 Nitrogen uptake at harvest

Figure 29 provide an overview of nitrogen uptake, expressed in kilograms per hectare (kg ha^{-1}). These measurements pertain to onions cultivated within each plot, each subject to distinct nitrogen fertilization treatments, denoted as _140, _90, VRA_A, and VRA_B. It is important to highlight that the upper and lower bounds on the graph signify the maximum and minimum fertilization levels.

Results show that N uptake was on average approximately 150 kg ha^{-1}, with the lowest value observed in VRA-A. However, it's important to note that these figures represent the average values, and further statistical analysis is required to assess the significance of these differences accurately.

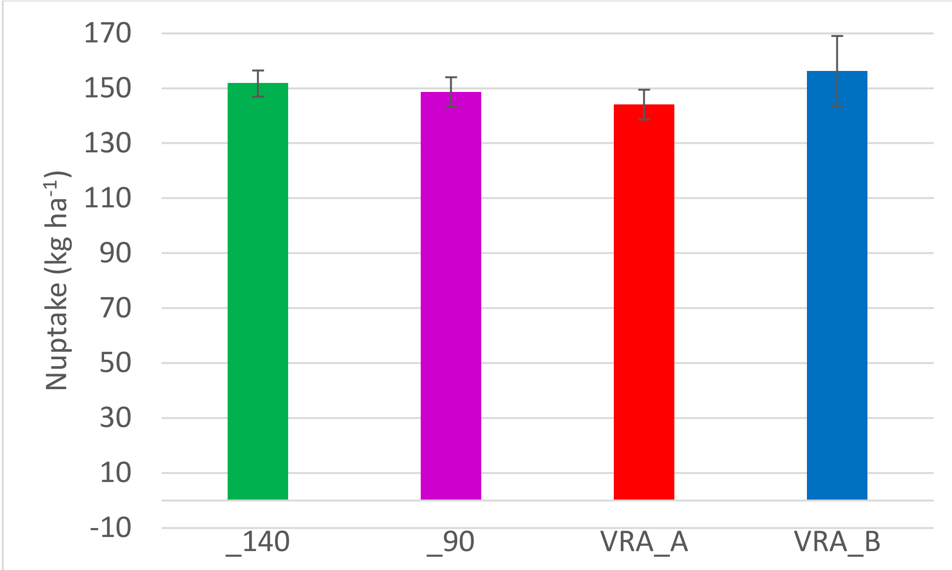

Figure 29 Nitrogen uptake (kg ha^{-1}).

The spatial variability of the N uptake is emphasized in the map here below, that shows how some plots have a low uptake despite receiving the highest input (e.g., _140 in the northeastern side,138 kg N ha^{-1}) while others had uptakes ≥ 170 kg N ha^{-1} nearby (VRA-B and _90).

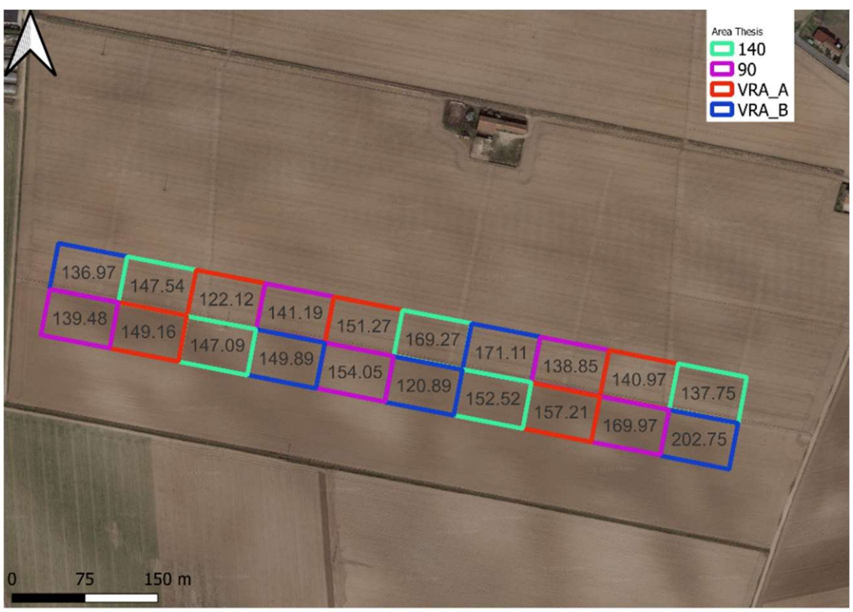

Figure 30 Map of nitrogen uptake (kg ha^{-1}) in the different tested plots.

4.10 Nitrogen use efficiency

The subsequent graph illustrates nitrogen use efficiency (NUE), calculated as the ratio between N bulb uptake and the N input obtained from total N fertilization amount.

Upon inspection of the graph, it becomes apparent that treatment _90 exhibits the highest NUE value among the various treatments, outperforming the others. This initial observation might suggest that treatment _90 boasts the most efficient nitrogen utilization, while treatment VRA_A appears to have the lowest efficiency. However, after conducting rigorous statistical analyses, it was established that there are no statistically significant differences in nitrogen use efficiency ($p = 0.06$) among the various treatments. In general, the average NUE was close to 80%.

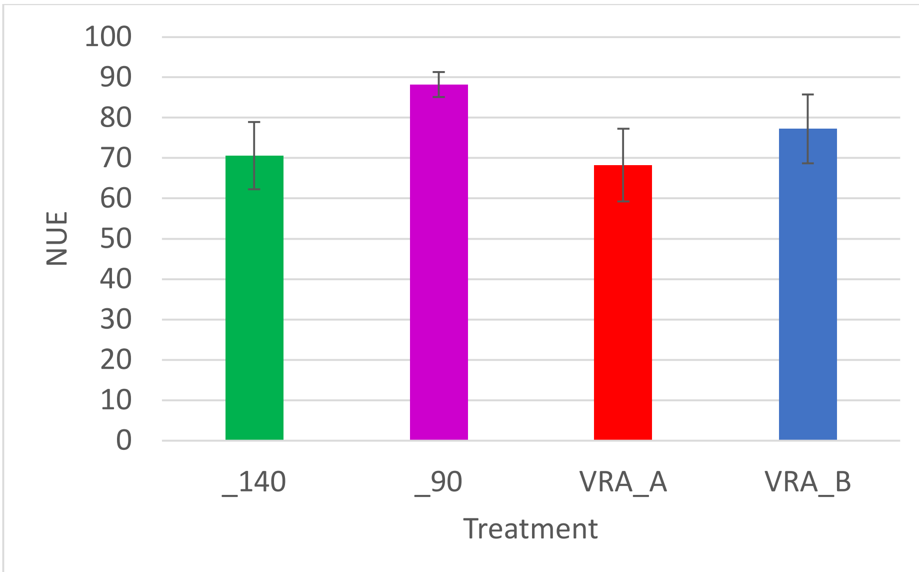

Figure 31 Nitrogen Use Efficiency.

Figure 32 Map of NUE in the different tested plots.

5. Conclusion

The comprehensive assessment of onion growth and yield in response to varying N fertilizer application rates was facilitated by the combined analysis of soil chemical properties, maps, and yield data. The integration of advanced methodologies, including remote sensing, GIS analysis, and some crop growth model – despite simple- was useful in optimizing N application strategies to enhance crop productivity while minimizing environmental impacts.

Key findings derived from this experiment include:

1. Yield variability: although it was observed some variation in average yields among different fertilization treatments, these differences lacked statistical significance. This outcome can be attributed to the substantial spatial variability which makes the approach useful to provide prescription maps, but also lacks of investigations about the yield potential in each homogeneous zone that might be defines based on historical yield data and soil variability.

2. Nitrogen uptake and nitrogen use efficiency (NUE): even for nitrogen, no statistically differences were observed for the total N uptake, while some slight difference was observed in terms of NUE ($p = 0.06$) when the lowest dose was applied.

These findings underscore the importance of contextualizing our results within the broader framework of precision agriculture. The complexities arising from spatial and temporal field variability introduce challenges that may obscure subtle treatment effects. Consequently, while our observations hint at variances in average values, the absence of statistical significance emphasizes the necessity for further research to elucidate these intricacies.

Furthermore, our analysis revealed that the difference in total final biomass was not statistically significant across different treatments. This implies that the fertilization rate could potentially be reduced. Notably, the highest nitrogen use efficiency was attained at the lowest N fertilization rate, suggesting the need for a judicious evaluation of the trade-off between fertilizer costs and selling prices.

In conclusion, this study represents a substantial stride towards refining precision nitrogen fertilization practices in onion cultivation. By harnessing cutting-edge technologies and analytical methodologies, we have provided a foundational framework for more informed and sustainable agricultural practices. Future research endeavors should delve deeper into the intricacies of field variability and strive to enhance precision strategies for optimizing both quantity and quality of onion yield. The pursuit of precision agriculture remains a dynamic and ongoing journey, with each study contributing invaluable insights to this ever-evolving field.

With specific regard to remote sensing using drones, our study established a promising relationship between NDVI, N content, and total biomass in onion cultivated in open-field conditions. This encourages the adoption of proximal or remote sensing technologies as cost-effective means to monitor vegetation status and, potentially, to provide N fertilizer prescriptions for onion fields. Consequently, our findings hold promise for increasing the sustainability of onion farms, with implications for economic and environmental sustainability.

6. Acknowledgement

I extend my heartfelt appreciation to my esteemed supervisor, Prof. Nicola Dal Ferro, for his unwavering support, valuable insights, and continuous guidance throughout the journey of my Master's thesis. His dedication, patience, and wealth of knowledge have been pivotal in shaping the course of my research. His encouragement, enthusiasm, and motivation have been a constant source of inspiration.

I am also immensely grateful to Carlo and Maria Elena and especially my girlfriend, Donya, whose assistance and contributions in both the laboratory and field have been indispensable to the success of my research endeavors. Their collaboration has enriched the practical aspects of my study.

Furthermore, I would like to convey my sincere gratitude to the entire faculty of Professors and Researchers who have imparted their wisdom and expertise during my studies in sustainable agriculture at the University of Padova (UNIPD). Their teachings have laid a strong foundation for my academic growth.

This research journey has been truly fulfilling, owing to the guidance, support, and encouragement of these individuals. Their collective efforts have significantly enriched my academic pursuits and have contributed to the successful completion of this thesis.

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8. List of figures