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INTEGRATING DRONE-BASED REMOTE SENSING, MACHINE LEARNING AND BAYESIAN MODELING TO ADVANCE PRECISION AGRICULTURE

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Summary

Section 1. General overview	3
<i>References</i>	<i>5</i>
Section 2. Introduction and theoretical background.....	6
<i>Drones in vegetable crops: a systematic literature review</i>	<i>6</i>
<i>Abstract</i>	<i>6</i>
<i>Introduction.....</i>	<i>7</i>
<i>Drones in agriculture</i>	<i>8</i>
<i>Materials and methods</i>	<i>11</i>
<i>Results</i>	<i>17</i>
<i>Discussions.....</i>	<i>48</i>
<i>Conclusions</i>	<i>49</i>
<i>References</i>	<i>50</i>
Section 3. Crop health and stress monitoring.....	62
<i>Spatiotemporal variability of nitrogen nutrition index in potato fields: a UAV-based machine learning approach using a bayesian critical nitrogen dilution curve</i>	<i>62</i>
<i>Abstract</i>	<i>62</i>
<i>Introduction.....</i>	<i>63</i>
<i>Materials and methods</i>	<i>66</i>
<i>Results</i>	<i>78</i>
<i>Discussions.....</i>	<i>84</i>
<i>Limitations, challenges and future research directions</i>	<i>89</i>
<i>Conclusions</i>	<i>91</i>
<i>Supplementary materials</i>	<i>92</i>
<i>References</i>	<i>96</i>
<i>Vineyard vegetative characteristics evaluation through UAV-based LiDAR SLAM technology</i>	<i>102</i>
<i>Abstract</i>	<i>102</i>
<i>Introduction.....</i>	<i>102</i>
<i>Materials and methods</i>	<i>104</i>
<i>Results and discussions</i>	<i>106</i>
<i>Conclusions</i>	<i>109</i>
<i>References</i>	<i>110</i>
<i>Spectral and thermal canopy characterization of different grapevine varieties</i>	<i>111</i>
<i>Abstract</i>	<i>111</i>
<i>Introduction.....</i>	<i>111</i>
<i>Materials and methods</i>	<i>113</i>
<i>Results and discussions</i>	<i>115</i>
<i>Conclusions</i>	<i>119</i>
<i>References</i>	<i>120</i>
<i>Olive tree canopy assessment by UAV multispectral images before and after pruning.....</i>	<i>121</i>
<i>Abstract</i>	<i>121</i>
<i>Introduction.....</i>	<i>121</i>
<i>Materials and methods</i>	<i>123</i>
<i>Results and discussions</i>	<i>125</i>
<i>Conclusions</i>	<i>128</i>
<i>References</i>	<i>128</i>
Section 4. Yield and biophysical parameters estimation.....	130
<i>Bayesian yield mapping and uncertainty analysis in vineyards using remote sensing data and grape harvester tracking</i>	<i>130</i>
<i>Abstract</i>	<i>130</i>
<i>Introduction.....</i>	<i>131</i>
<i>Materials and methods</i>	<i>135</i>

<i>Discussions.....</i>	<i>158</i>
<i>Limitations and perspectives.....</i>	<i>166</i>
<i>Conclusions.....</i>	<i>169</i>
<i>References.....</i>	<i>169</i>
<i>Ground truth sampling methods affect accuracy of UAV-based vineyard yield estimation: a case study..</i>	<i>175</i>
<i>Abstract.....</i>	<i>175</i>
<i>Introduction.....</i>	<i>176</i>
<i>Materials and methods.....</i>	<i>179</i>
<i>Results.....</i>	<i>185</i>
<i>Discussions.....</i>	<i>193</i>
<i>Limitations and future perspectives.....</i>	<i>196</i>
<i>Conclusions.....</i>	<i>196</i>
<i>References.....</i>	<i>197</i>
<i>Sustainable soil management in viticulture: a case study.....</i>	<i>201</i>
<i>Abstract.....</i>	<i>201</i>
<i>Introduction.....</i>	<i>202</i>
<i>Materials and methods.....</i>	<i>203</i>
<i>Results and discussions.....</i>	<i>205</i>
<i>Conclusions.....</i>	<i>209</i>
<i>References.....</i>	<i>209</i>
<i>Pruning weight estimation using multispectral sensors in a vineyard in southern Italy.....</i>	<i>211</i>
<i>Abstract.....</i>	<i>211</i>
<i>Introduction.....</i>	<i>211</i>
<i>Materials and methods.....</i>	<i>212</i>
<i>Results and discussions.....</i>	<i>216</i>
<i>Conclusions.....</i>	<i>220</i>
<i>References.....</i>	<i>220</i>
Section 5. Development of prescription maps for precision agriculture	221
<i>Developing high-resolution nitrogen prescription maps using UAV-based multispectral data and dilution curve approach.....</i>	<i>221</i>
<i>Abstract.....</i>	<i>221</i>
<i>Introduction.....</i>	<i>222</i>
<i>Materials and methods.....</i>	<i>223</i>
<i>Results and discussions.....</i>	<i>226</i>
<i>Conclusions.....</i>	<i>229</i>
<i>References.....</i>	<i>230</i>
<i>Fertilisation prescription map in olive orchard using UAV multispectral camera.....</i>	<i>231</i>
<i>Abstract.....</i>	<i>231</i>
<i>Introduction.....</i>	<i>232</i>
<i>Materials and methods.....</i>	<i>233</i>
<i>Results and discussions.....</i>	<i>235</i>
<i>Conclusions.....</i>	<i>239</i>
<i>References.....</i>	<i>239</i>
Section 6. Final Remarks	241

Section 1. General overview

Over the next twenty-five years, global agriculture must achieve an unprecedented dual objective: increase food output by roughly 50 % to feed almost 10 billion people by 2050, while simultaneously reducing greenhouse-gas emissions, safeguarding increasingly scarce soil and water resources, and restoring degraded ecosystems (FAO, 2023).

Precision Agriculture (PA) is the primary technological pathway to meet this challenge. PA is defined as a “*management strategy that gathers, processes and analyses temporal, spatial and individual plant and animal data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production*” (ISPA, 2024). PA applies the “4 Rs”: the right input, at the right rate, in the right place, at the right time, thereby curbing fertiliser and pesticide use, reducing irrigation demand, and limiting environmentally harmful losses through emissions and leaching.

The effectiveness of PA relies on the ability to quantify and manage the intrinsic spatial and temporal heterogeneity of agro-ecosystems, a task for which remote sensing (RS) is indispensable. By exploiting crop geometrical features or spectral signatures, RS enables retrieval of plant-health indicators; reflectance in specific spectral regions from which widely used vegetation indices (Vis) can be derived, is tightly linked to key physiological parameters (Weiss et al., 2020).

RS encompasses a diverse ecosystem of sensors and platforms. Satellite platforms provide large-scale coverage at 10–30 m ground sampling, whereas unmanned aerial vehicles (UAVs) yield centimetre-scale imagery with resolution set by altitude, optics, and mission design (Colomina and Molina, 2014a). RS sensors are predominantly electro-optical systems that detect and record upwelling radiation from the surface across the visible, near-infrared and short-wave infrared, and in some applications the microwave domain. Except for the active Lidar, which emits laser pulses to generate 3D point clouds, most sensors employ passive imaging cameras, including RGB, multispectral, hyperspectral and thermal sensors (Olson and Anderson, 2021).

These technologies, however, generate vast and complex datasets that require sophisticated post-processing. Before extracting actionable information, satellite, UAV and in-situ data must

be harmonised through quality control, geometric, radiometric and atmospheric correction and orthorectification process (Verrelst et al., 2015).

The resulting data are heterogeneous, noisy and complex. Managing them for PA, while modelling and quantifying spatiotemporal variability, requires specialised methods; among these, geostatistical frameworks and machine learning (ML) are most widely used (Domingues et al., 2022; Fei et al., 2023b; Paudel et al., 2021). ML has emerged as the key tool for discovering functional links between RS signals and plant physiological processes in agroecosystems. By leveraging flexible, non-linear models, ML integrates data from multiple sources (climate, soil and crop), capturing interactions and thresholds that escape simple parametric models (Zhang et al., 2024). This allows RS observations to be translated into estimates of canopy condition, nitrogen requirements or yield estimations, considering spatial and temporal heterogeneity. Deep learning (DL) extends ML with neural networks that learn representations from massive, unstructured data and support computer vision algorithms and autonomous decision-making (Ferro et al., 2024a; Odebiri et al., 2021).

Alongside to ML and DL, other modelling families have matured. A major class comprises process-based models, which encode mechanistic crop–soil–atmosphere interactions (e.g., mass and energy balances, phenology, water and nitrogen flows) via differential equations; others adopt probabilistic frameworks (Cammarano et al., 2023). Among these, Bayesian models provide a tool capable of combining prior knowledge with heterogeneous observations and explicitly quantifying uncertainty. Rather than treating probability as long-run frequency, Bayesian inference updates beliefs through Bayes’ theorem, yielding a posterior distribution over parameters and predictions. Hierarchical structures pool information across environments, varieties and years, improving robustness and generalisability under complex datasets, typical of agroecosystems (Bürkner, 2018).

Taken together, these elements delineate a research context in which high-resolution RS, modelling and agronomic decision support systems are becoming progressively integrated. UAV-derived indicators, multi-sensor information, ML and Bayesian approaches address distinct yet complementary dimensions of crop monitoring and management, and their combined use would reinforce the analytical foundation required to make informed agronomic decision.

In this context, the present thesis aims to develop advanced agronomic-management frameworks based on RS to promote sustainable production and mitigate climate-change impacts on agriculture. The research focus on integrating UAV-multispectral data with ML techniques and Bayesian models to enhance the precision management of several agroecosystem across Europe. First, a systematic literature review will delineate the spectrum of UAV applications in horticulture and identify how drones contribute to PA development in this context. Subsequently, study cases on different agroecosystems will implement key applications, such as crop health and stress monitoring, the estimation of yield and biophysical parameters and the production of prescription maps. All the study cases presented are based on approaches that couple UAV-based data with several ML or Bayesian models. Through targeted case studies, the spatial and temporal variability of these parameters are assessed, and innovative algorithm and data-based procedures are introduced to refine management practices within PA context. The resulting knowledge will help make agriculture more sustainable and resilient, aligning it with the demands of data-driven, technology-enabled food production.

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Section 2. Introduction and theoretical background

Drones in vegetable crops: a systematic literature review

Abstract

In the context of increasing global population and climate change, modern agriculture must enhance production efficiency. Vegetables production is crucial for human nutrition and has a significant environmental impact. To address this challenge, the agricultural sector needs to modernize and utilize advanced technologies such as drones to increase productivity, improve quality, and reduce resource consumption. These devices, known as Unmanned Aerial Vehicles (UAV), with their agility and versatility play a crucial role in monitoring and spraying operations. They significantly contribute to enhancing the efficacy of precision farming.

The aim of this review is to examine the critical role of drones as innovative tools to enhance management and yield of vegetable crops cultivation. This review was carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework and involved the analysis of a wide range of research published from 2018 to 2023. According to the phases of Identification, Screening, and Eligibility, 132 papers were selected and analysed. These papers were categorized based on the types of drone applications in vegetable crop production, providing an overview of how these tools fit into the field of Precision Farming. Technological developments of these tools and data processing methods were then explored, examining the contributions of Machine and Deep Learning and Artificial Intelligence. The review pointed out the significance of drone applications in vegetable crops and the immense potential of these tools in enhancing cultivation efficiency. Drone utilization enables the reduction of input quantities such as herbicides, fertilizers, pesticides, and water but

also the prevention of damages through early diagnosis of various stress types. These input savings can yield environmental benefits, positioning these technologies as potential solutions for the environmental sustainability of vegetable crops.

Keywords: Artificial Intelligence, horticulture, precision agriculture, PRISMA, UAV.

Introduction

In the past decades, precision agriculture has emerged as a significant solution to address the increasingly pressing challenges associated with agricultural production, including the production of vegetable crops. With climate change posing threats to agricultural resources and a steadily growing global population, the need to efficiently and sustainably enhance food production becomes essential. According to the report "Future of Food and Agriculture: Alternative Pathways to 2050" by the United Nations Food and Agriculture Organization (FAO), the global population is projected to reach nearly 10 billions by 2050, leading to a corresponding increase in demand for food crops (FAO, 2023). At the same time, the surfaces and water resources available for agriculture are becoming increasingly scarce (Chakraborty and Newton, 2011; FAO, 2023). In this scenario, society places immense pressure on agriculture, driving towards increased crop yields without compromising quality, while simultaneously reducing operational costs and global pollution.

Within the agricultural context, vegetables play a primary role; indeed, they are considered protective foods, providing essential nutrients to the human diet due to their richness in vitamins, fibres, minerals, and nutraceuticals (Dias, 2012). Furthermore, regular consumption of fruits and vegetables contributes to the risk reduction of numerous diseases, including cardiovascular diseases and cancer (Aune et al., 2017).

Overall efficient and sustainable cultivation techniques become necessary. Precision agriculture plays a paramount role among the techniques that are transforming agricultural production and can be regarded as one of the most promising solutions (Finger et al., 2019).

In this context, there is a growing adoption of advanced and intelligent techniques and technologies, such as artificial intelligence and unmanned aerial vehicles (UAVs) (Kutyaauripo et al., 2023). UAVs have become one of the most versatile sensing platforms in horticulture; nonetheless, they operate alongside other monitoring systems that are already well established within farm operations. This coexistence highlights that the adoptability of drones is influenced

not only by their technological capabilities but also by practical considerations, including regulatory requirements, operational constraints, and the need for seamless integration into existing workflows.

Despite these factors, UAVs significantly enhance cultivation processes, as they can perform monitoring and spraying missions, thus optimizing the efficiency of pesticide, fertilizer, and water usage. They promptly identify stress induced by pests, diseases, nutritional and water deficiencies, while also facilitating the spraying procedure (Radoglou-Grammatikis et al., 2020). The applications of UAVs in agriculture are different and include nearly all agricultural productions. For example, applications in viticulture, olive cultivation, orchards, herbaceous crops, as well as vegetable cultivation, are well-established (Catania et al., 2023a; Ferro et al., 2023; Gonzalez-Dugo et al., 2013; Messina et al., 2021; Roma et al., 2023b; Torres-Sánchez et al., 2014).

The main objective of this review is to analyse how drones can be employed in precision agriculture concerning vegetable crops. This study aims to provide a critical and comprehensive synthesis on the topic through a systematic literature review of the last six years, focusing on the key objectives that can be achieved using drones in this field.

Drones in agriculture

Drones are currently one of the most representative technologies in the evolution of precision agriculture in the scientific and productive world. However, their history began in other fields of application. The drone, in fact, originated as a tool to be employed in the military sector, aiming to safeguard the integrity of human personnel in reconnaissance and surveillance missions. Over time, their use has extended well beyond the military context, finding applications in various sectors, including entertainment, transportation, security, photography, and environmental exploration (Floreano and Wood, 2015).

The most common designation is "Unmanned Aerial Vehicles" (UAV). They can also be defined by other acronyms, many of which are of Anglo-Saxon origin: in addition to "Remotely Piloted Aircraft System" (RPAS), they may be referred to as "Unmanned Aerial System" (UAS), "Aerial Robot" or simply "Drone" (Colomina and Molina, 2014b).

These terms refer to a complex system consisting of the aerial platform, one or more components and/or sensors making up the payload, and a ground station in communication with

the flight controller of the platform. Within the flight controller, components dedicated to the orientation and movement of UAVs are present, including gyroscopes, magnetic compass, GNSS module, pressure sensor, and triaxial accelerometer (Casa, 2016).

UAVs are generally categorized based on various attributes they possess, including aircraft types, wing types, take-off/ landing direction, payloads, flying altitude, etc (Korchenko and Illyash, 2013).

According to the classification by Watt et al. (2012), they can be distinguished as MAV (Micro (or Miniature) or NAV (Nano) Air Vehicles), VTOL (Vertical Take-Off & Landing), LASE (Low Altitude, Short-Endurance), LALE (Low Altitude, Long Endurance), MALE (Medium Altitude, Long Endurance), HALE (High Altitude, Long Endurance).

The platforms most used in precision agriculture fall into the LASE class and are fixed-wing systems or multirotor, such as helicopters, quadcopters, hexacopters, octocopters, etc. VTOL multirotor platforms, widely employed for crop monitoring, generally weigh less than 5 kg excluding the payload, are equipped with interchangeable lithium batteries, and are easily transportable, facilitating movement between different fields.

UAV platforms can be controlled by the operator through the ground station, remaining in the field of vision, or they can fly in automatic mode, following a trajectory defined by the user through waypoints during the flight plan design phase.

Payloads can include sensors and cameras for data collection or even specialized equipment for tasks such as crop spraying [Section 4.7]. Although the sensors that can be equipped on drones are numerous, the most commonly used on UAV platforms for agricultural purposes are:

- Visible cameras, RGB (Red, Green and Blue): These are the simplest cameras capable of producing grayscale or color images for characterizing the visible properties of plants and their growth (Bendig et al., 2014; Zarco-Tejada et al., 2014).

- Multispectral cameras: Capable of producing images in different bands of the spectrum. These cameras typically cover the visible (VIS) and Near InfraRed (NIR) portions of the spectrum, with which it is possible to calculate most vegetation indices used in agriculture. Many of these indices have been used by different authors in the works included in this review, and they are summarized in the following table (Catania et al., 2023a; Ferro and Catania, 2023a).

Table 1. Summary of Vegetation Indices included in this review.

Index	Long Name	Equations	References
NDVI	Normalized Difference Vegetation Index	$\frac{\rho 800 - \rho 680}{\rho 800 + \rho 680}$	(J. W. Rouse et al., 1974)
TVDI	Temperature Vegetation Dryness Index	$\frac{(Ts - Ts \min)}{(a + b \left(\frac{\rho 550 - \rho 680}{\rho 550 + \rho 680} \right) - Ts \min)}$	(Sandholt et al., 2002)
RVI	Simple Ratio Index	$\frac{\rho 800}{\rho 680}$	(Birth and McVey, 1968)
GNDVI	Green Normalized Difference Vegetation Index	$\frac{\rho 800 - \rho 550}{\rho 800 + \rho 550}$	(BUSCHMANN and NAGEL, 1993)
OSAVI	Optimized Soil Adjusted Vegetation Index	$(1 + 0.16) * \frac{\rho 800 - \rho 680}{(\rho 800 + \rho 680 + 0.16)}$	(Zou and Möttus, 2017)
SAVI	Soil Adjusted Vegetation Index	$\frac{\rho 800 - \rho 680}{\rho 800 + \rho 680 + L} * (1 + L)$	(Huete, 1988)
NGRDI	Normalized Green Red Difference Index	$\frac{\rho 550 - \rho 680}{\rho 550 + \rho 680}$	(Hunt et al., 2005)
MSR	Modified Simple Ratio	$\frac{((\rho 800 / \rho 680) - 1)}{\sqrt{\left(\left(\frac{\rho 800}{\rho 680} \right) + 1 \right)}}$	(Chen, 1996)
MCARI	Modified Chlorophyll Adsorption Ratio Index	$((\rho 730 - \rho 680) - 0.2 * (\rho 730 - \rho 550)) * (\rho 730 / \rho 680)$	(Daughtry et al., 2000)
C_{green}	Chlorophyll Index green	$\left(\frac{\rho 800}{\rho 550} \right) - 1$	(Gitelson et al., 2003)
C_{rededge}	Chlorophyll Index red edge	$\left(\frac{\rho 800}{\rho 730} \right) - 1$	(Gitelson et al., 2003)
CCCI	Canopy Chlorophyll Content Index	$((\rho 800 - \rho 730) / (\rho 800 + \rho 730)) / ((\rho 800 - \rho 550) / (\rho 800 + \rho 550))$	(Wolanin et al., 2019)
GLI	Green Leaf Index	$\frac{2 \rho 550 - \rho 680 - \rho 450}{2 \rho 550 + \rho 680 + \rho 450}$	(Louhaichi et al., 2001)
NDRE	Normalized Difference Red Edge	$(\rho 800 - \rho 730) / (\rho 800 + \rho 730)$	(Ustuner et al., 2014)
TBI (530, 734, 514)	Three-band Spectral Index	$\frac{\rho 530 - \rho 734}{\rho 734 + \rho 514}$	(Dash and Curran, 2004)
WDVI	Weighted Difference	$\rho 800 - (a * \rho 680)$	(Clevers, 1991)

	Vegetation Index		
PRI	Photochemical Reflectance Index	$\frac{\rho_{531} - \rho_{570}}{\rho_{531} + \rho_{570}}$	(Gamon et al., 1992)
RDVI	Renormalized Difference Vegetation Index	$\frac{(\rho_{800} - \rho_{680}) / \sqrt{(\rho_{800} + \rho_{680})}}{1.2}$	(Raun et al., 2001)
MTVI 1	Modified Triangular Vegetation Index 1	$1.2 [1.2 (\rho_{760} - \rho_{580}) - 2.5(\rho_{650} - \rho_{580})]$	(Haboudane et al., 2004)
CWSI	Crop Water Stress Index	$\frac{(T_c - T_a) - (T_c - T_a)_{LL}}{(T_c - T_a)_{UL} - (T_c - T_a)_{LL}}$	(Jackson et al., 1988)
ExG	Excess Greenness Index	$\left(\frac{(2 * \rho_{550}) - \rho_{680} - \rho_{450}}{\rho_{680} + \rho_{550} + \rho_{450}} \right)$	(Woebbecke et al., 1995)

-Hyperspectral cameras: This type of sensor provides images in a high number of bands with very high spectral resolution, detecting a vast amount of information. The application of these cameras allows for in-depth analysis of crops, providing information on the presence of various pathogens (Adão et al., 2017; Calderón et al., 2013).

-Thermal cameras: Provide images with information about the temperature of each pixel. These sensors enable the identification of thermal alterations on the leaf surface induced by water stress conditions, making them particularly useful for water management (Javier Baluja et al., 2012; Gago et al., 2015).

-Laser Imaging Detection and Ranging (LiDAR): These are active sensors that leverage the physical operating principle of Radio Detection and Ranging (RaDAR). In particular, these sensors emit a light pulse (laser, in the case of LiDAR) or microwaves (Radar) and measure, using a detector, the return of the pulse reflected by the target, calculating the time taken (Sankey et al., 2017; van Zadelhoff et al., 2007). These sensors provide physical measurements of the geometry and volumes of canopies (Christiansen et al., 2017).

Materials and methods

A systematic literature search method was employed to compose this review, following the guidelines set forth by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (<https://doi.org/10.1136/bmj.n71>, Consulted on May 3rd, 2023) (Page et al., 2021). The research method encompassed identification, screening and eligibility procedures. This systematic analysis of the literature was chosen due to its methodical, replicable, and

comprehensive approach. This method aims to mitigate bias risks through precise and exhaustive literature searches, thereby offering a transparent and scientifically rigorous process. Moreover, it provides a detailed account of the procedures followed by the authors.

Identification

The research was conducted in May 2023. The Scopus database was used to perform the systematic review. Titles, abstracts and keywords were used as the search fields within the Scopus electronic database. The query used in the search encompassed 112 fields (as detailed in the document '[Query ricerca bibliografica Review.docx](#)'). The chosen keywords were selected based on preliminary research and their demonstrated usefulness in finding relevant articles.

Furthermore, the results obtained from Scopus were filtered with the following criteria: (1) The paper was published between 2018 and 2023, (2) The paper was not a review or conference review, (3) The paper was not a book or book chapter, (4) The paper was not a letter, erratum, data paper, note, (5) The paper was not a conference paper. In total, 864 papers were identified, and the search results were saved in the Scopus database for subsequent analyses. The process followed is shown in Figure 1.

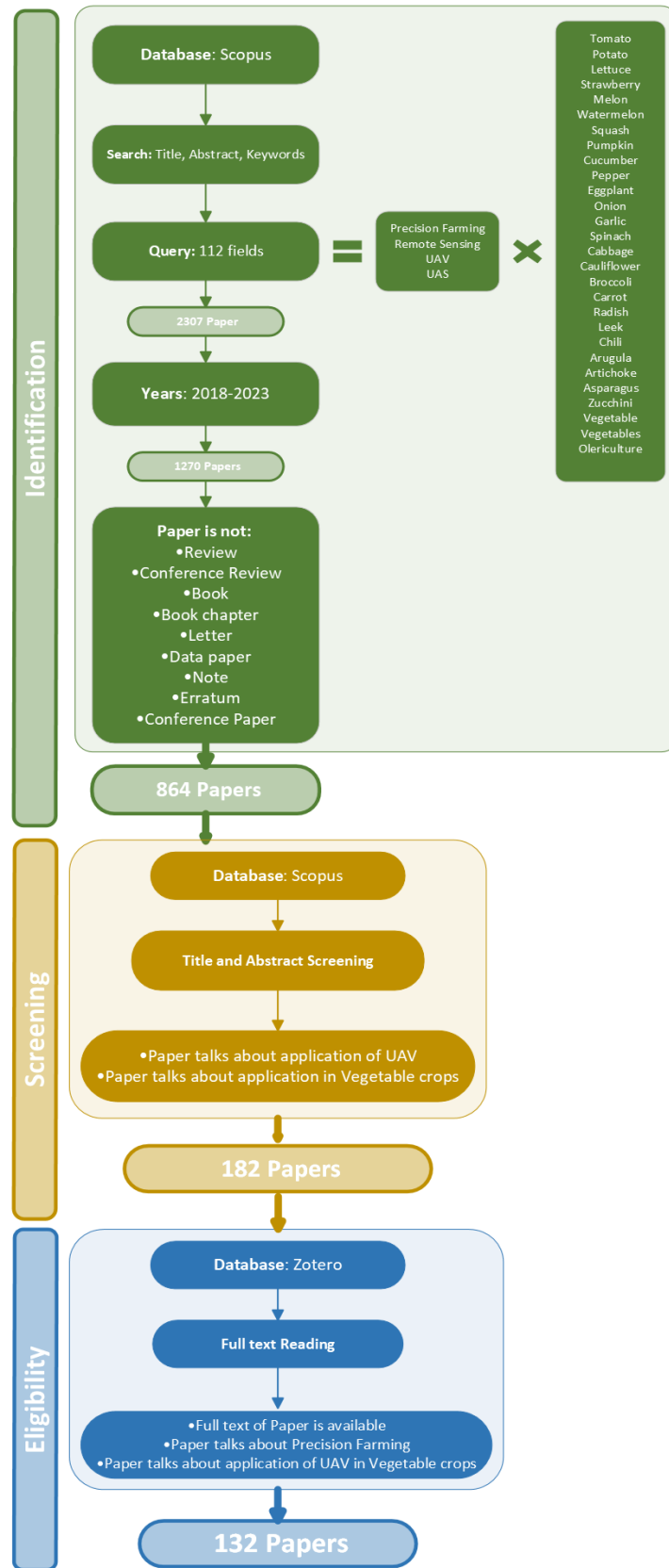


Figure 1. Flowchart illustrating the consecutive stages and results of the identification, screening, and eligibility procedures.

Screening

The authors reviewed the titles and abstracts of all the 864 articles found. The inclusion criteria and progression to the next stage were: (1) The paper included UAV applications, (2) The paper included applications on vegetable crops. Out of the previously selected 864 papers, only 182 met the criteria. These papers were exported to the personal Zotero library.

Eligibility

The authors examined all the 182 papers by reading the entire text of each paper. Papers with the following characteristics were excluded: (1) The full text was not available, (2) The paper did not actually involve the use of drones in vegetables cultivations, (3) The paper did not pertain to precision agriculture applications. In this phase, 50 papers did not meet the criteria, while 132 articles were used as the foundation for conducting this review.

Data analysis

The 132 papers that successfully passed the Identification, Screening, and Eligibility stages were exported to Excel. Data analysis was conducted using this software to consolidate the results from various studies on the topic of this review. The following data were extracted from each study: Title, Author, Year, analysed Species, Family, Study purpose, Sensor type(s), Sensor spectral range, Number of sensor bands, post-processing techniques, Vegetation indices, and results obtained. The data extracted during this phase were analysed and evaluated. The data analysis revealed heterogeneity in the objectives obtained by using drones, and they were summarized into seven goals as described in section 4.

Through data analysis, significant trends in this field of study have been identified. Figure 2 graphically represents the distribution of the papers based on the crop families studied. 52% of the papers focused on UAV applications within the Solanaceae family, underscoring the central role of crops like potatoes, tomatoes, peppers, and eggplants in both scientific research and agricultural production. The Brassicaceae family ranks second at 13%, encompassing crops like cabbage, cauliflower, and radish. Subsequently, there are Cucurbitaceae (9%), Amaryllidaceae (8%), Amaranthaceae (6%), Rosaceae (5%), Asteraceae (5%), and Apiaceae (2%).

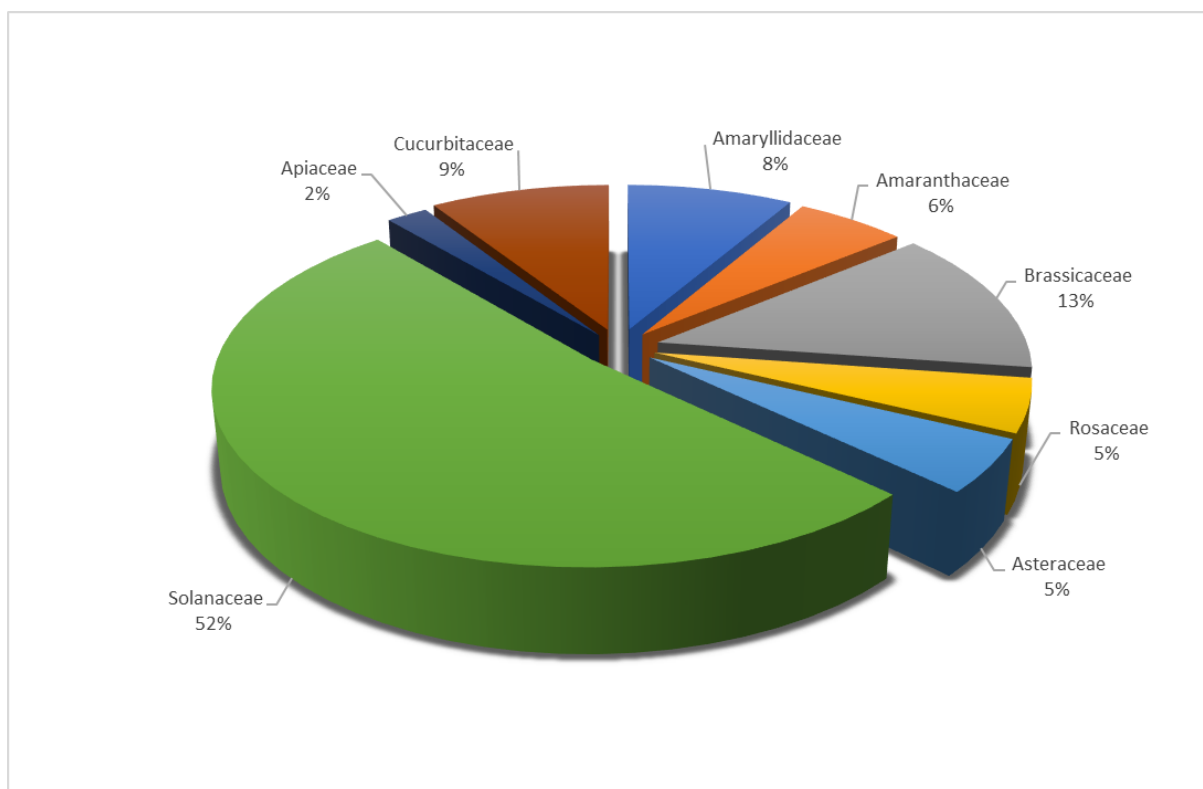


Figure 2. Distribution of the papers based on the families of the species under study, along with their percentages.

In this phase, an analysis of the bibliographic sources was conducted, with a particular focus on evaluating the journals and conferences included. For each journal or conference within the review, the evaluation parameters on the Scopus platform were examined to assess the relevance of the utilized sources. This platform calculates scientific journals relevance using three key parameters:

CiteScore: this index measures the average citations received per document published within the considered series.

Source Normalized Impact per Paper (SNIP): this parameter assesses the citations received relative to the expected citations for the series' subject field, thereby normalizing the impact of citations within the context of the relevant discipline.

Scimago Journal Rank (SJR): this index measures the weighted citations received by the series, taking into account both the subject field and the prestige of the citing series. The citation weighting is contingent on the subject field and the prestige (SJR) of the citing series.

The indices, referred to 2022, were extracted for each journal included in the review and are summarized in table 2.

Table 2. Summary of Relevance Indices of source of papers.

Source title	N. of Papers	CiteScore	SJR	SNIP
Acta Horticulturae	2	0.5	0.149	0.167
Agricultural Water Management	5	10.7	1.524	2.018
Agriculture	4	3.6	0.561	1.162
Agronomy	9	5.2	0.663	1.215
Agronomy Journal	2	4.3	0.586	0.889
American Journal of Potato Research	1	4.6	0.39	0.938
Applied Sciences	2	4.5	0.492	0.974
Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping	4	0.7	0.166	0.235
Biosystems Engineering	1	10.1	1.061	1.931
Canadian Journal of Remote Sensing	1	3.9	0.619	0.651
Computers and Electronics in Agriculture	7	13.6	1.587	2.473
Drones	2	6.1	0.845	1.884
Engineering in Agriculture, Environment and Food	1	4.9	0.325	0.568
European Journal of Remote Sensing	1	7	0.66	1.131
Field Crops Research	1	9.6	1.396	2.001
Frontiers in Plant Science	10	7.1	1.231	1.580
Horticulturae	2	2.4	0.487	0.969
International Journal of Advanced Computer Science and Applications (IJACSA)	1	2.1	0.258	0.512
International Journal of Applied Earth Observation and Geoinformation	4	10.2	1.628	1.833
International Journal of Remote Sensing	3	7	0.732	1.030
IOP Conference Series: Earth and Environmental Science	1	0.8	0.197	0.255
ISPRS Journal of Photogrammetry and Remote Sensing	1	19.2	3.308	3.280
Journal of Applied Remote Sensing	2	3.4	0.388	0.564
Journal of Biosciences	1	4.8	0.586	0.599
Journal of Experimental Botany	1	12	1.823	1.619
Journal of Sensors	1	2.6	0.366	0.774
Journal of Unmanned Vehicle Systems	1	N/A	N/A	N/A
Multidimensional Systems and Signal Processing	1	5.2	0.516	1.045
PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science	1	6.4	0.801	1.172
Plant Disease	1	4.5	0.677	1.058
Plant Methods	2	10.6	1.121	1.904
Plant Phenomics	1	12	1.341	1.563
PLOS ONE	1	6	0.885	1.253

Precision Agriculture	9	11.1	1.209	2.183
Remote Sensing	25	7.9	1.136	1.532
Remote Sensing for Agriculture, Ecosystems, and Hydrology XXI	1	0.7	0.166	0.235
Sensors	3	6.8	0.764	1.317
Smart Agricultural Technology	9	2.6	N/A	0.666
Soft Computing	1	7.7	0.819	1.349
Spanish Journal of Agricultural Research	1	1.9	0.249	0.55
Spatial Information Research	1	4	0.448	0.851
Sustainability	1	5.8	0.664	1.198
Sustainable Computing: Informatics and Systems	1	8	0.869	1.515
The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	2	1.8	0.274	0.427

Results

The selected papers under review have been categorized into seven distinct groups. Each of these categories represents a specific task that drones can undertake within the realm of precision agriculture applied to vegetable crops. Each task is addressed as an individual section within this review. These sections are arranged in a logical sequence. Initially, the papers pertaining to UAV applications for crop monitoring throughout their growth cycles are discussed. In particular, the first section deals with crop identification and segmentation within images captured by drones, with the same principles applied to weed detection in the "Crop and Weed Detection" (section 4.1). Subsequently, papers primarily focused on photogrammetry are described in the "Morphological and Geometrical Feature Extraction" (section 4.2). Then, papers related to "Crop Health and Stress Monitoring" (section 4.3) are addressed, followed by "Disease and Pest Scouting" (section 4.4), "Water Management" (section 4.5), and finally leading to papers concerning yield estimation in the section titled "Yield, Biomass, and Ripening Estimation" (section 4.6). Additionally, papers that explore the applications of UAVs as tools for aerial spraying are discussed in a separate section titled "Aerial Spraying" (section 4.7).

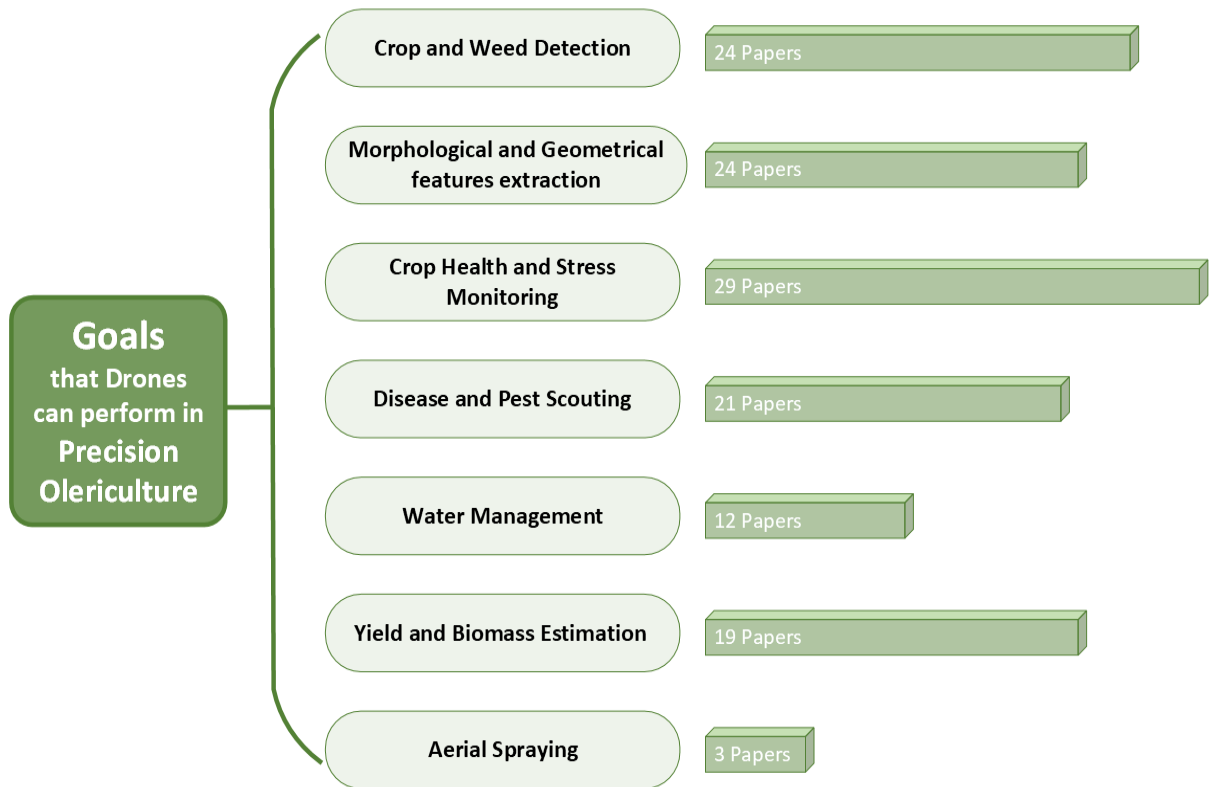


Figure 3. Distribution of the papers based on their research goals, with the number of articles within each section.

Figure 3 illustrates the goals achievable by drones in Precision agriculture applied to vegetable crops, along with the respective number of dedicated papers. Specifically, the most extensively studied category was “Crop Health and Stress Monitoring”, followed by “Crop and Weed Detection” and “Morphological and Geometrical Feature Extraction”. “Aerial Spraying” was indeed the category with the fewest number of dedicated papers, despite a growing scientific interest in this topic.

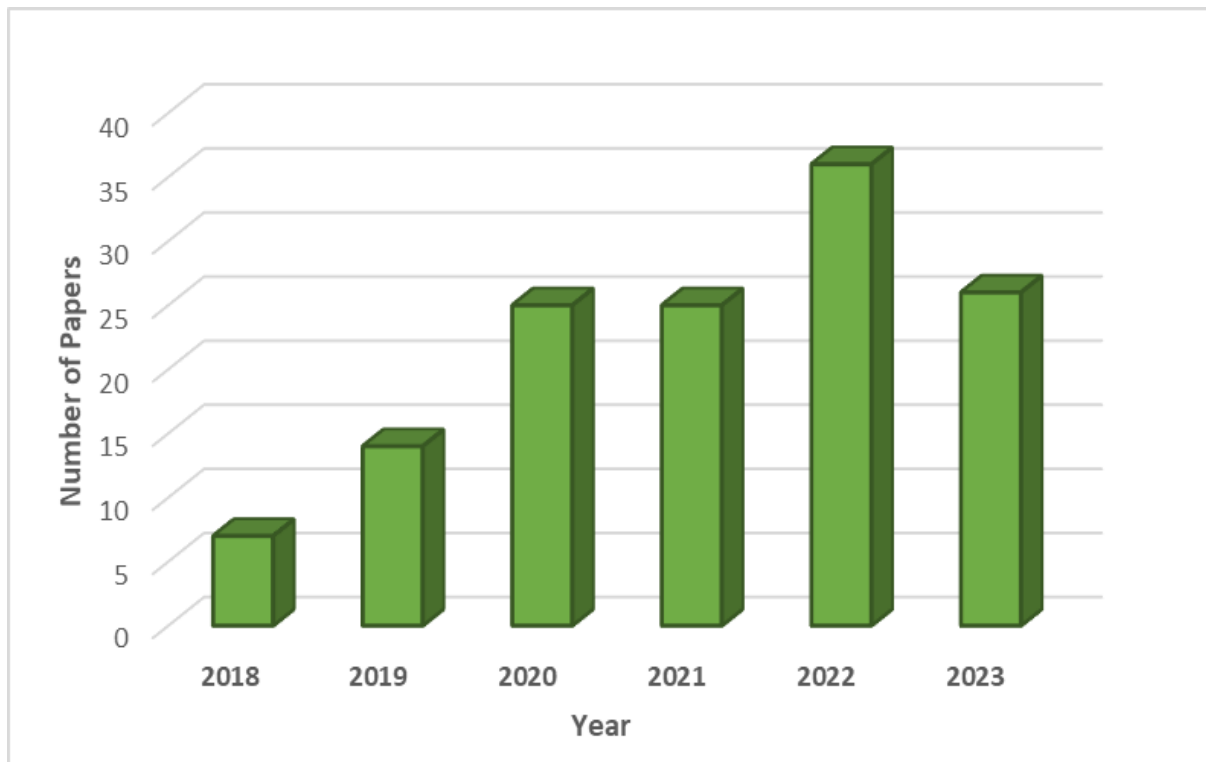


Figure 4. Paper distribution per year in the period 2018-2023.

Figure 4 shows the distribution of the examined papers by year. A clear upward trend is evident from 2018 to 2022, with 36 papers published in 2022 and 26 papers published by mid-2023, as compared to 7 and 14 papers published in 2018 and 2019, respectively.

Crop and weed detection

Table 3 shows an overview of the different algorithms used by the examined authors with reference to Crop and Weed Detection. For each reference, the best algorithm among the ones that were tested is reported, together with its accuracy.

Table 3. Overview of different algorithms used by authors for Crop and Weed Detection.

Specific Task	Crop	Method/ best algorithm	Accuracy	References
Detection of ROI: extracting crop from image	Carrot; Cabbage; Spinach; Potato	Attention Based Recurrent Convolutional Neural Network (ARCNN)	92.80% (OA)	(Feng et al., 2020)
	Cabbage	DeepLab V3+	0.9 (MIoU)	(Jo et al., 2021)
	Tomato	Local maxima Extraction and Baesyan Segmentation	0.98 (OA)	(Ronchetti et al., 2020)
	Onion e Garlic	CIE L*a*b* color space and mean shift (MS)	84.6% (ASP)	(Kim et al., 2023)

	Zucchini	OCRNet	mIoU 94.4%	(Huang et al., 2021)
	Cabbage	Mask R-CNN	86.63% (mAP)	(Ye et al., 2023)
	Onion	Random Forest (RF)	91.20 (PA)	(Modica et al., 2021)
	Chili	prototypical network	96.46 % (LA)	(D. Zhang et al., 2022)
Plant counting, density estimation	Spinach	Excess Green Index and Otsu thresholding methods + AlexNet	98.6 % (OA)	(Valente et al., 2020)
	Potato	Mask R-CNN	0.781 (MOTA)	(Machefer et al., 2020)
	Lettuce	Mask R-CNN	0.918 (MOTA)	(Machefer et al., 2020)
	Strawberry	Fully convolutional network (FCN)	0.67 (PPMC)	(Barreto et al., 2021)
	Potato	Excess Green Index and Otsu thresholding methods	0.96 (R ²)	(Li et al., 2019)
	Potato	Faster Region-based Convolutional Neural Network (FRCNN) framework	0.80 (R ²)	(Mhango et al., 2021)
Weed detection	Cabbage	Convolutional Neural Network (CNN)	92.41 % (OA)	(Ong et al., 2023)
	Strawberry	Improved faster R-CNN	95.3% (AA)	(Khan et al., 2021a)
	Onion	You Only Look Once (YOLOv3)	93.81% (AP)	(Parico and Ahamed, 2020)
	Lettuce	Regression between total cover values (25 calibration images) and total weight measured	HC	(Pallottino et al., 2020)
	Pepper	U-Net	71.20 % (MIoU)	(Gutiérrez-Lazcano et al., 2022)
	Onion	Maximum Likelihood (ML) and Support Vector Machine (SVM) algorithms	< 85 % (OA)	(Rozenberg et al., 2021)
	Spinach	visual transformers (ViT)	99.63 % (OA)	(Reedha et al., 2022)
	Strawberry	Semi-Supervised Generative Adversarial Network (SGAN)	90 % (AA)	(Khan et al., 2021b)
	Spinach	CNNs, Residual Network (ResNet)	94.34 % (AUCs)	(Bah et al., 2018)
	Spinach, pepper	Faster RCNN	98.3 % (CA)	(Ajayi and Ashi, 2023)
	Spinach, pepper	You Only Look Once (YOLO) v5s,	0.712 (AP)	(Ajayi et al., 2023)

Overall accuracy (OA); Mean intersection over union (MIoU); Average Segmentation Performance (ASP); Object Detection Accuracy (mAP); Segmentation Accuracy (PA); Location Accuracy (LA); Multiple Object Tracking Accuracy (MOTA); Hight Correlation (HC); Pearson Product Moment Correlation Coefficient (PPMC); Correlation Coefficient (R2); Average Accuracy (AA); Average Precision (AP); Area Under Curve (AUCs); Classification Accuracy (CA).

Crop detection

When utilizing images acquired through UAV to extract information about plant morphology or health, they must undergo a processing procedure. One of the initial crucial steps in this process is Crop Detection (Feng et al., 2020). Crop detection refers to crop identification, classification, segmentation, and/or mapping (Jo et al., 2021). This process allows for isolating the crop of interest, referred to as Region Of Interest (ROI), within the images, while excluding everything that is not ROI, known as the background (Ronchetti et al., 2020). This background could simply be the soil, but it can also be highly heterogeneous. For instance, Kim et al. (Kim et al., 2023) extracted the canopy of onions and garlic from a complex background consisting of plastic mulch, soil, and shadows under varying lighting conditions. Huang et al. (Huang et al., 2021) recognized the canopy of zucchinis intercropped with sunflowers. Regarding the methodologies employed to extract the crop from high-resolution images captured by drones, two primary categories can be distinguished: object-based methods, such as Object-Based Image Analysis (OBIA) or Geographic Object-Based Image Analysis (GEOBIA), and pixel-based methods, which primarily utilize Machine Learning and Deep Learning algorithms (Fig. 5) (Ye et al., 2023).

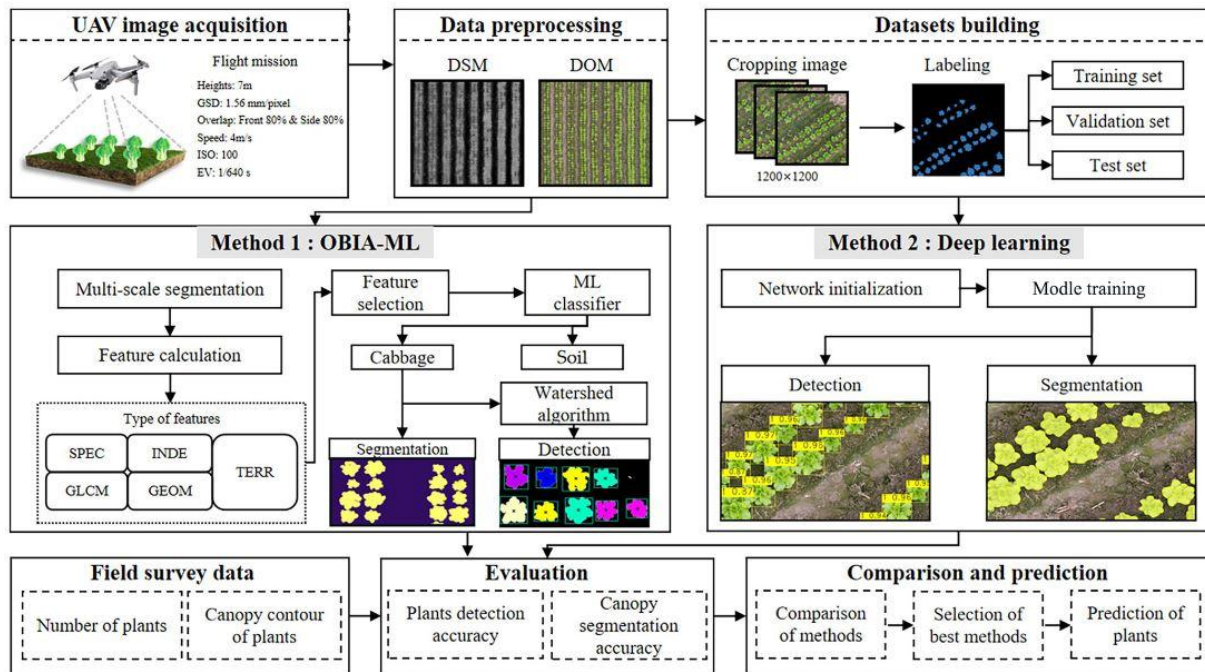


Figure 5. Crop extraction processes framework (Ye et al., 2023).

Modica et al. (2021) compared and evaluated different object-based methods and machine learning algorithms for segmenting and classifying onion crops, achieving the best results with Support Vector Machine (SVM) and Random Forest (RF) algorithms. Valente et al. (2020) proposed an automatic machine vision method to identify and count spinach plants. This method, through the combination of Otsu's method and transfer learning Convolutional Neural Network (CNN), achieved an accuracy of 95%. Machefer et al. (2020) on the other hand, used a Mask R-CNN for plant counting and sizing in potato and lettuce, achieving a multiple object tracking accuracy (MOTA) of 0.78 for potato plants and 0.91 for lettuces. This evaluation metric has the advantage to synthesize other error sources such as false positives, missed plants and identity switches, allowing for the assessment of the performance of object detection algorithms (Bernardin and Stiefelhagen, 2008).

Through these methodologies, it is possible to monitor the development of crops from the early growth stages, estimating the seedling percentage through seedling identification. For instance, D. Zhang et al. (2022) developed a detection framework based on a prototypical network for chili seedling crop detection, achieving a location accuracy of 96.46%. Barreto et al. (2021) extended a fully automatic method for counting maize seedlings to strawberries, with prediction errors lower than 4%. For the estimation of potato crop emergence, Li et al. (2019) developed a semi-automatic image analysis software, obtaining results comparable to manual field assessment ($r^2 = 0.96$). In addition to evaluating crop emergence and seedling identification, it is also possible to monitor plant density variation throughout the season, as demonstrated by Mhango et al. (2021) in a study conducted on potatoes.

Once the crop is identified, it becomes feasible to proceed with various other tasks, both of photogrammetric and spectral nature, which are individually addressed in the subsequent sections.

Weed detection

The effective control of weeds is of paramount importance in agriculture, which is why the use of herbicides is widespread. However, to reduce herbicide usage, a method called "site-specific weed management" (SSWM) is increasingly gaining traction (Johnson et al., 1997). This approach capitalizes on the fact that weeds are not uniformly distributed within a field but tend to form clusters, providing a significant opportunity for herbicide savings (Swinton, 2005). The

use of high-resolution images acquired through drones enables efficient identification and differentiation of weeds from the main crop. This aspect has garnered attention from various authors who have conducted different studies employing different methodologies and applying them to various types of vegetables crops. For instance, Ong et al. (2023) in cabbage cultivation, Khan et al. (2021a) in strawberry cultivation, and Parico and Ahamed (2020) in onion cultivation. These systems have also been implemented in protected environments; Pallottino et al. (2020), for example, estimated the exact weed amount on baby-sized red lettuce under a polyethylene multi-tunnel greenhouse using a light drone.

Another interesting application was observed in a study conducted by Gutiérrez-Lazcano et al. (2022). These authors successfully identified and segmented *Cuscuta* spp. plants, a worldwide-distributed weed known to pose problems for various types of crops.

The methodologies employed for weed detection rely on classification algorithms that discriminate between weeds, the main crop, and the background. These algorithms can be categorized into three main groups: supervised, semi-supervised, and unsupervised, based on how the labelling process for generating the training dataset occurs. Rozenberg et al. (2021) used two supervised classification algorithms, Maximum Likelihood (ML), and Support Vector Machine (SVM), for weed identification in onion fields. A significant challenge of supervised methods is the need for a sufficiently large dataset to train the model, which is a time-consuming and tedious task. To address this issue, Reedha et al. (2022) proposed a Visual Transformers (ViT) approach to reduce the size of the labelled dataset, demonstrating the potential of this method in weed classification in beet, parsley, and spinach fields. Khan et al. (2021b), on the other hand, introduced a new semi-supervised method, an algorithm that generates an additional training dataset for model training. This method achieved an accuracy of 90% for classifying weeds in pea and strawberry fields with 80% of the training data left unlabelled.

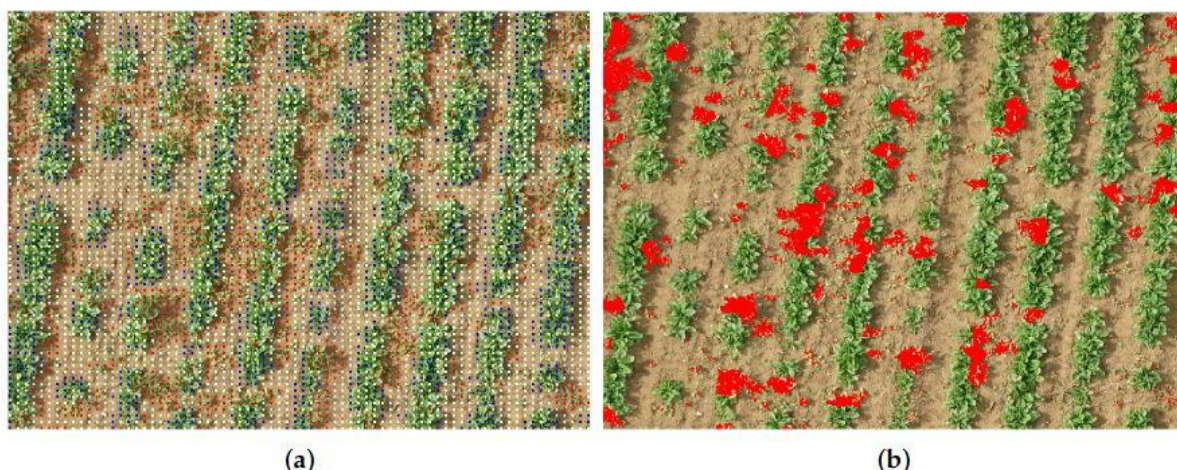


Figure 6. UAV image classification with models by unsupervised data in a spinach field. (a) samples obtained after using a sliding window, without crop line and background information. Blue, red, and white dots mean that the plants are identified as crop, weed, and an uncertain decision, respectively. (b) in red the weeds detected after crop line and background information has been applied (Bah et al., 2018).

Regarding non-supervised methods, Bah et al. (2018) proposed a fully automatic learning method (unsupervised) for weed detection (Fig. 6); this method yielded results comparable to supervised methods in tests conducted in spinach fields, with only 1.5% differences in accuracy. In training a deep learning model, the number of epochs required to train accurate and robust algorithms must be considered. In a study evaluating the effect of the number of epochs in Faster Region-Based Convolutional Neural Network on weed classification accuracy, Ajayi and Ashi (2023) observed that an increasing number of epochs significantly improved weed classification accuracy in various crops, including pepper and spinach. Additionally, Ajayi et al. (2023) assessed the impact of the number of training epochs on YOLO (You Only Look Once), identifying 600 as the optimal epochs for achieving the best performance.

Following the preceding steps, it is possible to generate prescription maps for herbicide distribution, which can be used for the implementation of SSWM through the use of aerial spraying or machinery equipped with Variable Rate Technology (VRT) (R. B. Brown and J.-P. G. A. Steckler, 1995).

Morphological and geometrical features extraction

Phenotyping is the process of evaluating both the plant physical and morphological characteristics and their phenological stage. Drones can capture high-resolution images of crops and analyse them to extract information about size, shape, architecture, and even phenological stage (table 4).

Table 4. Morphological and geometrical crop parameter extracted from remote sensing images for specific task and crop.

Specific Task	Crop	Crop Parameter Used	References
Phenotyping	Potato	Canopy Height and Crop Coefficient	(Malachy et al., 2022)
		Canopy ground cover, height and volume	(de Jesus Colwell et al., 2021)
		Lead Area Index	(Roosjen et al., 2018)
		Lead Area Index	(Zhu et al., 2019)
	Tomato	Canopy Height and Crop Coefficient	(Malachy et al., 2022)
		Canopy Cover and Height	(Enciso et al., 2019)
		Canopy Height	(Moeckel et al., 2018)
		Lead Area Index	(Antonucci et al., 2023)
	Melon	Lead Area Index	(Zhu et al., 2019)
	Cauliflower	Head diameter, Height and Curvature	(Grenzdörffer, 2019)
		Head Volume	(C. Zhou et al., 2022)
	Cabbage	Canopy Length and Width	(J. Zhang et al., 2022)
		Canopy Height	(Moeckel et al., 2018)
	Eggplant	Canopy Height	(Moeckel et al., 2018)
	Lettuce	N.S.	(Mascarenhas Maciel et al., 2019)
Canopy Biomass Estimation	Potato	Canopy height and textures	(Yang Liu et al., 2022)
	Potato	Canopy height and Fractional vegetation cover	(Luo et al., 2022)
	Potato	Number of leaves	(S. Yang et al., 2023)
	Strawberry	Canopy Area, height and volume	(Zheng et al., 2022)
	Onion	Green canopy cover, height and volume	(Ballesteros et al., 2018)
Spraying volume Determination	Potato	Canopy coverage and height	(Xie et al., 2022)
Growth Status Monitoring	Cabbage	Canopy Height and Vegetation Fractions	(Kim et al., 2018)

	Cabbage	Canopy height	(Jamil et al., 2022)
	Radish	Canopy Height and Vegetation Fractions	(Kim et al., 2018)
	Pumpkin	Canopy height	(Jamil et al., 2022)
	Broccoli	Canopy Cover, spectral features	(Lee et al., 2023)
Phenological stage recognition	Potato	Canopy height	(Martins et al., 2023)
	Cucumber, muskmelon, squash, pumpkin and watermelon	Approach based on Deep Learning Classification Algorithm	(Mithra and Nagamalleswari, 2023)
	Lettuce		(Han et al., 2021)
	Onion		(Din et al., 2021)

Zhang et al. (J. Zhang et al., 2022) mapped the dimensions of cabbage, estimating length and width, using a multispectral camera-equipped drone at an altitude of 10 m with a spatial resolution of 5 cm. Din et al. (Din et al., 2021) recognized the growth stage of onions combining deep learning techniques with multispectral data. Meanwhile, Kim et al. (Kim et al., 2018) utilized UAV-RGB based imagery with a spatial resolution of 0.64 cm at an altitude of 20 m for estimating biophysical properties of cabbage and radish.

Through image analysis techniques, photogrammetry, machine and deep learning algorithms, specific crop parameters can be calculated. Among these parameters, estimating plant height has been a sought-after goal for several authors. Jamil et al. (2022) estimated the height of cabbage and pumpkin plants using UAV-based RGB imagery, achieving excellent correlations with field-measured data, with r^2 values of 0.86 and 0.94, respectively for cabbage and pumpkin. Moeckel et al. (2018) obtained r^2 values ranging from 0.87 to 0.97 on eggplant, tomato, and cabbage. Enciso et al. (Enciso et al., 2019) achieved r^2 values of 0.98, 0.97, and 0.99 in three different tomato varieties, confirming the reliability and accuracy of these tools for plant height estimation. Malachy et al. (2022) compared four different methods for extracting single height crop values from Crop Height Model (CHM) and subsequently estimating the crop coefficient (K_c) in both potato and tomato crops. Among these four methods (Mean, Sample, Median, and Peak), the Mean and Sample ones emerged as the best crop height predictors ($R^2=0.84$ and 0.80 , respectively).

Also Leaf Area Index (LAI) has been estimated in different studies. Roosjen et al. (2018) assessed LAI in potato fields, and Zhu et al. (2019) in four different crops, including potatoes and melons. The latter achieved excellent correlation with field-measured data, with an r^2 of

0.85 and a root mean square error (RMSE) of $0.41 \text{ m}^2/\text{m}^2$. Certain crops, such as cauliflowers, allow for precise and rapid aerial geometric characterization due to their upward-oriented and exposed plant structure and head shape. This factor facilitates the rapid and accurate monitoring of large areas, providing detailed information about plant phenology, as confirmed by studies conducted by several authors (Grenzdörffer, 2019; Lee et al., 2023; C. Zhou et al., 2022).

One of the direct applications that can be derived from having biometric parameters such as plant area, height, and volume resides in the capability to readily estimate crop biomass. This parameter has been estimated, for example, in strawberry cultivation by Zheng et al. (2022) and in onion cultivation by Ballesteros et al. (2018). Some tubers, like potatoes, growing underground, prevent direct characterization of productive organs. As a result, estimating plant geometry and above-ground biomass is of great interest for the agronomic insights it can provide (Yang Liu et al., 2022; Luo et al., 2022; S. Yang et al., 2023).

Indeed, by combining metrics like Canopy Coverage and Plant Height, it is possible to estimate the appropriate spraying volume (Xie et al., 2022).

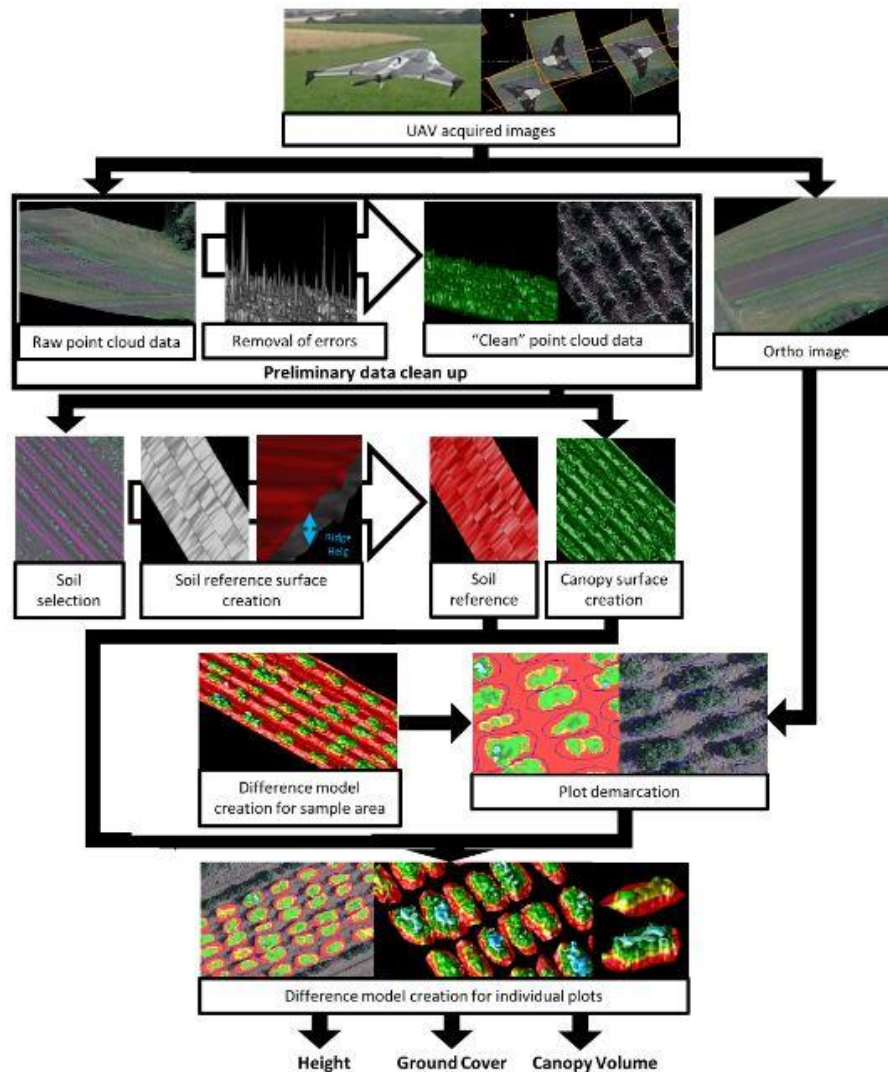


Figure 2. Acquisition of quantitative data on potato plant canopy structure using a Structure from Motion algorithm from UAV acquired images in (de Jesus Colwell et al., 2021).

Rapid phenotyping can also be an excellent tool for breeders: De Jesus Colwell et al. (2021) developed a method to demonstrate how the use of point cloud data obtained from low-cost UAV images can be employed to create 3D surface models of plant canopies on potatoes, from which all morphological and geometric characteristics can be extrapolated, paving the way for a large-scale expansion of future genotype-phenotype association studies (Fig.7). An efficient application of drone-based phenotyping has been observed in tomatoes, where it was utilized to assess the effectiveness of certain biostimulants (Antonucci et al., 2023). In lettuce, image phenotyping was employed to evaluate inbred lines with varying carotenoid content (Mascarenhas Maciel et al., 2019). Through the identification of plant morphological characteristics, it is also possible to identify specific phenological stages. In potatoes, it was possible to determine the onset of tuberization, a crucial phenological stage for adapting

irrigation management, by calculating plant height detected by drone (Martins et al., 2023). Identifying specific phenological stages like flowering can be particularly important for cucurbits, where the flower represents one of the final products. For this purpose, Mithra and Nagamalleswari (2023) developed a transfer learning algorithm using the *CuCuFlower* dataset, capable of identifying the genus and gender of 9 cucurbit species, including cucumber, muskmelon, squash, pumpkin, and watermelon. Detecting flowering can also be significant for crops where the flowering process is pivotal for genetic improvement actions, as in the case of lettuce (Han et al., 2021).

Crop health and stress monitoring

In vegetables cultivations, one of the fields where drone usage has become more established and widespread is the accurate and geospatial assessment of plant health and stress levels (table 5).

Table 5. Overview of the papers included in this section, divided by specific task, species, and family.

Family	Species	Specific Task	References
Solanaceae	Potato	Crop health and stress monitoring	(Théau et al., 2020), (Meivel and Maheswari, 2022), (Butte et al., 2021), (Coelho et al., 2022), (Farooque et al., 2023)
		Chlorophyll content	(Li et al., 2020), (Yang et al., 2022), (Yin et al., 2023)
		Nitrogen status	(Peng et al., 2021), (Fan et al., 2022), (Hunt et al., 2018), (J. Zhou et al., 2022), (Fan et al., 2023)
	Tomato	Crop health and stress monitoring	(Garcia-Garcia et al., 2021), (Fullana-Pericàs et al., 2022), (Kasper Johansen et al., 2019), (Marconi et al., 2019)
		Chlorophyll content	(Angel and McCabe, 2022)
	Pepper	Crop health and stress monitoring	(Sosa-Herrera et al., 2019)
	Eggplant	Crop health and stress monitoring	(Mwinuka et al., 2022)
Brassicaceae	Cabbage	Crop health and stress monitoring	(Sinde-González et al., 2022), (Lee et al., 2020)
		Nitrogen status	(Besand and Katroschan, 2023)
Amaryllidaceae	Onion	Crop health and stress monitoring	(Messina et al., 2021), (Messina et al., 2020; Ryu et al., 2020)
Asteraceae	Lettuce	Chlorophyll content	(Bhandari et al., 2020)
Apiaceae	Carrot	Nitrogen status	(Metiva et al., 2023)
Amaryllidaceae	Garlic	Crop health and stress monitoring	(Ryu et al., 2020)
Cucurbitaceae	Squash	Crop health and stress monitoring	(Sharaf-Eldin et al., 2023)

This practice has proven to be one of the most common and rooted applications in vegetable cultivation (Sosa-Herrera et al., 2019) and today it can be carried out with various methodologies and using different sensors. For instance, in potato cultivation, Théau et al. (2020) employed a thermal infrared sensor for stress scouting and calculated the Temperature Vegetation Dryness Index (TVDI), resulting in accurate scouting maps. Meivel and Maheswari (2022) used a multispectral camera and calculated various vegetation indices, including Normalized Difference Vegetation Index (NDVI). Meanwhile, Butte et al. (2021) proposed a deep learning algorithm named Retina-Unet-Ag, capable of detecting healthy and diseased plants, with an average Dice Score Coefficient (DSC) of 0.74.

The scientific community has increasingly recognized the solid connections between measurable parameters through these platforms and the degree of plant health. Many recent studies, in fact, use UAVs as tools for evaluating and quantifying plant responses to specific treatments. For instance, crop's response to different irrigation treatments was evaluated by Garcia-Garcia et al. (2021) in tomato cultivation; they used NDVI to estimate the dynamics of Canopy Cover (CC) with varying water supply, while Fullana-Pericàs et al. (2022) tested NDVI, Simple Ratio Index (SR), and Green Normalized Difference Vegetation Index (GNDVI) in combination with conventional leaf-level physiological and agronomic measurements in an experiment involving 91 different genotypes. In both studies, the indices showed excellent correlations with field-measured comparison data. Kasper Johansen et al. (2019), analysed biomass variation under different saline stress conditions in tomato cultivation, too (Figure 8). Marconi et al. (2019) investigated the capability of a UAV-RGB based crop monitoring system to determine the best management practices for three different tomato varieties by comparing different planting dates, plant density, use of plastic mulch, and fertilization rate, demonstrating these systems' ability to assess plant responses to treatments and select the best management practices.

Similar types of applications have been found in studies conducted on other crops: Mwinuka et al. (2022) used GNDVI, NDVI, and Optimized Soil Adjusted Vegetation Index (OSAVI) to assess the interactive effect of nitrogen and water in an eggplant field. Sharaf-Eldin et al. (2023) evaluated responses to water stress and potassium deficiency in squash using three-band Spectral Indices and a Machine Learning model. In potato, Coelho et al. (2022) employed NDVI as an indicator of crop development under varying calcium inputs. In cabbage cultivation, the effect of nano nutrient applications was determined by analysing their

relationship with various vegetation indices, including NDVI, GNDVI, Normalized Green Red Difference Index (NGRDI), and chlorophyll content, with good results (Sinde-González et al., 2022). A UAV with a multispectral sensor was used to monitor the crop cycle in onion cultivation by Messina et al. (2021) aiming to identify the optimal nitrogen input to maximize productivity. Specifically, the Soil-Adjusted Vegetation Index (SAVI) was employed for crop vigor monitoring, which also showed significant correlations with yield.

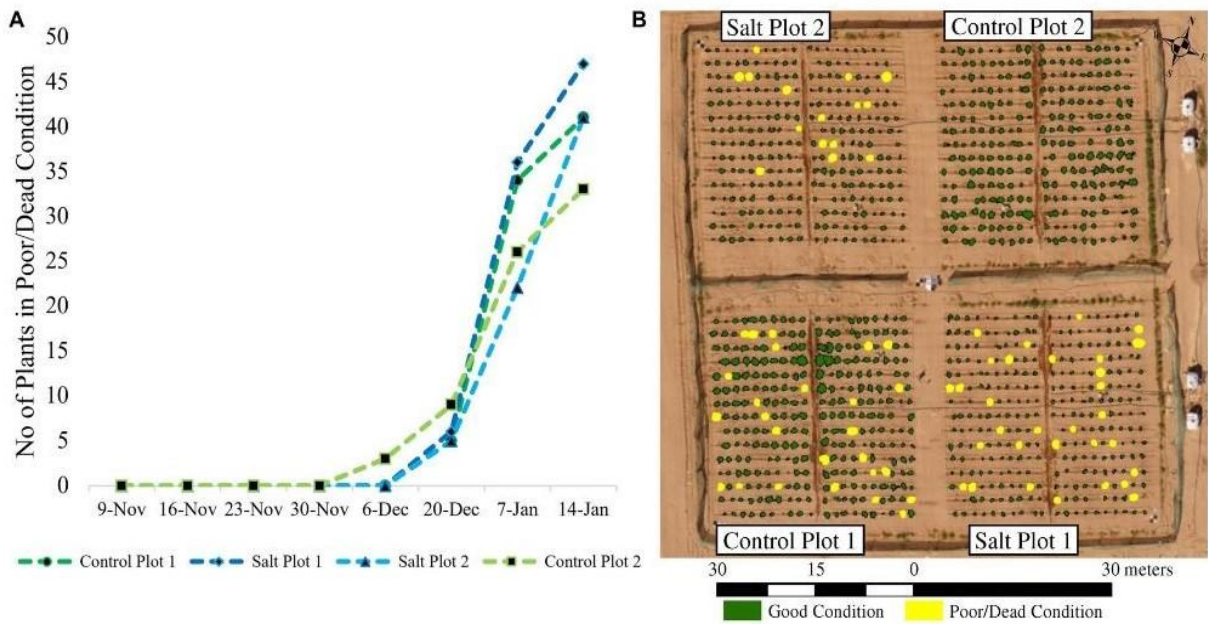


Figure 8. Salinity stress detection in tomato field. (A) Cumulative number of plants either missing or being in a poor/dead condition throughout the growing season; and (B) mapped plants in either good or poor/dead condition (Kasper Johansen et al., 2019).

Studies with different approaches have been identified on the topic of crop monitoring. Messina et al. (2020) and Ryu et al. (2020) compared NDVI maps derived from UAV and satellite platforms for monitoring onion and garlic crops. In both studies, the high resolution offered by drones provided advantages over satellite platforms, allowing for the removal of the soil effect on crop NDVI, which is not possible using images from satellite platforms. On the other hand, Farooque et al. (2023) proposed a method to translate images from an RGB sensor for calculating NDVI map. Lee et al. (2020) developed a calibration method for NDVI calculated from drone, using a handheld hyperspectral sensor. Specifically, the reflectance data measured in the field through a portable spectroradiometer were correlated with data measured from the drone, creating a calibration equation method for UAV spatial information. The calibration allowed the authors to create a precise normalized distribution vegetation index (p-NDVI) map.

Chlorophyll content

Chlorophyll is the essential pigment for photosynthesis and is responsible for plant's ability to capture solar energy. A high level of chlorophyll indicates efficient photosynthesis and a good state of leaf health and overall plant well-being, while low presence of this pigment may indicate stress or a problem. There are several methods to measure leaf chlorophyll levels; however, many of these are destructive and/or require human presence in the field. The Soil Plant Analysis Development (SPAD) method belongs to the latter category, which is widely used but demands the presence of a technician in the field and provides point measurements without georeferencing.

Drones equipped with multispectral and/or hyperspectral sensors, with their high resolution, provide precise and geospatialized measurements of chlorophyll content, enabling the creation of chlorophyll content maps for crops. Li et al. (2020) worked on a chlorophyll estimation method using hyperspectral data, providing two machine learning models. Specifically, they found that the Partial Least Squares (PLS) model achieved the best estimates of potato chlorophyll content in the bud stage and tuber-growth stage, while the Stepwise Regression (SR) model achieved the best estimates in the tuber formation stage and starch accumulation stage. Yang et al. (2022), using multispectral data and indices such as SAVI, Modified Simple Ratio (MSR), Simple Ratio Vegetation Index (RVI), and NDVI, combined with Machine Learning and a Stacking Ensemble Algorithm, managed to provide highly accurate chlorophyll content estimates. Yin et al. (2023) used UAV-based multispectral vegetation indices as input in models such as Random Forest (RF), Support Vector Regression (SVR), Partial Least Squares Regression (PLSR), and Ridge Regression (RR) to predict chlorophyll content in potato crops. Comparing the results with field-measured data using the SPAD chlorophyll meter, the authors achieved the best performance with RF, reaching an R^2 of 0.76 and a RMSE of 1.97.

Other researchers have conducted studies with the aim of identifying the most effective indices for this purpose. For instance, Bhandari et al (Bhandari et al., 2020) found the best performance with the Modified Chlorophyll Adsorption Ratio Index (MCARI) in a study conducted on lettuce. In the case of potato cultivation, Yin et al. (Yin et al., 2023) identified Chlorophyll Index green (CI_{green}) and Chlorophyll Index red edge ($CI_{red\ edge}$) as the best predictors of chlorophyll content. In tomatoes, Angel and McCabe (Angel and McCabe, 2022) developed a model that

utilizes machine learning algorithms for the retrieval of spatially and multi-temporal Leaf-Chlorophyll Dynamics.

Nitrogen status

Nitrogen is one of the most crucial elements within a crop system. A low concentration of this element in leaf tissues leads to hindered growth and stress. Optimal nitrogen management enhances yield and product quality while concurrently mitigating environmental risks associated with nitrogen leaching (Metiva et al., 2023). Swift and accurate estimation of nitrogen concentration in tissues is imperative for informed decision-making in fertilization management. UAVs, owing to their adaptable usage and high resolution, are potential tools to fulfil the role of a Decision Support System (DSS) in nitrogen management. In the context of potato cultivation, Peng et al. (2021) explored diverse platforms equipped with multispectral sensors for nitrogen management. They found UAVs to be valuable instruments in assessing indicators such as Plant Nitrogen Uptake (PNU), Plant Nitrogen Concentration (PNC), and Nitrogen Nutrition Index (NNI), ranking among the most precise and accurate platforms employed (Fig. 9).

On the other hand, Fan et al. (2022) employed visible light vegetation indices in combination with morphological parameters derived from an inexpensive UAV digital camera to estimate potato nitrogen content, achieving R^2 values up to 0.8. Contrary results were obtained by Hunt et al. (2018), who assessed the potential of NDVI and GNDVI as predictors of potato nitrogen status, yielding nonsignificant outcomes. In the case of cabbage cultivation, Besand and Katroschan (2023) identified strong correlations between indices such as Canopy Chlorophyll Content Index (CCCI), Green Leaf Index (GLI), Normalized Difference Red Edge (NDRE), and NDVI and Nitrogen Status.

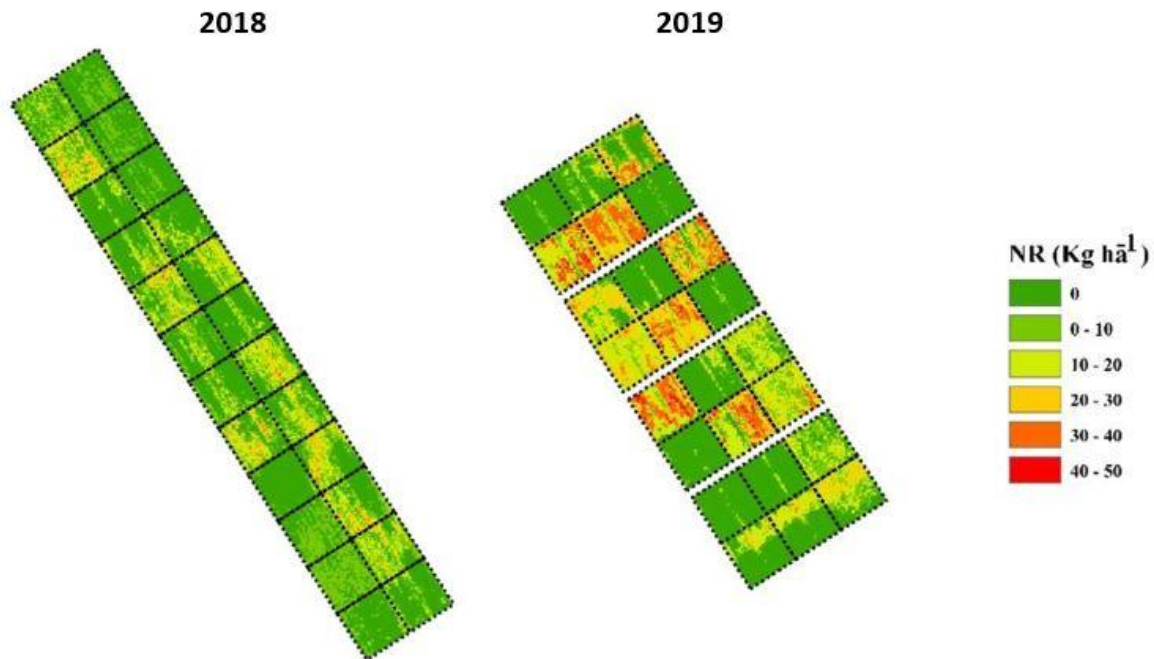


Figure 9. Nitrogen requirement maps for mid-season potato growth in field experiments predicted from UAV data in (Peng et al., 2021).

On the other hand, Zhou et al. (2022) focused on the evaluation and comparison of hyperspectral and multispectral images for potato nitrogen status estimation. These authors observed superior performance with hyperspectral imaging, achieving stronger correlations as the width of the utilized bands decreased. They also obtained that, within the spectrum, bands situated in the visible region exhibited higher sensitivity to changes in plant nitrogen content compared to those in the infrared region. The efficacy and precision of hyperspectral imaging were also affirmed by Fan et al. (2023b). They compared hyperspectral single-band reflectance with two- and three-band spectral indices for estimating potato nitrogen content, attaining optimal performance with the three-band spectral index (TBI5) (530, 734, 514).

Disease and Pest Scouting

Disease and pest management is a highly significant topic in agricultural crops. Particularly in vegetable crops, effective management of pests and diseases can lead to substantial reduction in the use of pesticides, offering substantial benefits for the environment and human health. However, an efficient, timely, and cost-effective scouting process is needed. Traditional scouting methods are labour-intensive and expensive, and do not always allow for timely

intervention. This is why contemporary olericulture often tends to overuse phytosanitary products, sometimes resorting to preventive treatments without actual necessity.

Remote Sensing stands out as one of the most advanced technologies to gather such information. Moreover, the utilization of drones equipped with high-resolution cameras represents one of the most efficient techniques for scouting. Drones enable high precision and promptness at relatively low costs, offering the capacity to assess disease or infestation progression both in space and time. Table 6 outlines all the identified applications, categorized according to the crop.

Table 6. Diseases and pests analysed by the authors, divided by species.

Species	Disease and Pest	Reference
Potato	Late blight (<i>Phytophthora Infestans</i>)	(Duarte-Carvajalino et al., 2018; Rodríguez et al., 2021)
	Early Die Complex (<i>Verticillium Wilt</i>)	(Lizarazo et al., 2023)
	PVY Virus	(Siebring et al., 2019)
	Soft Rot (<i>Erwinia carotovora</i>)	(Siebring et al., 2019)
	Early Blight (<i>Alternaria Solani</i>)	(Van De Vijver et al., 2022)
	Cyst Nematodes (<i>Globodera Pallida</i> , <i>G. Rostochiensis</i>)	(Jindo et al., 2023)
Tomato	Target Spot (<i>Corynespora Cassiicola</i>)	(Abdulridha et al., 2020a, 2020b)
	Bacterial Spot (<i>Xanthomonas Perforans</i>)	(Abdulridha et al., 2020a, 2020b)
	Late Blight (<i>Phytophthora Infestans</i>)	(de Oliveira Dias et al., 2023)
	Yellow Leaf Curl Virus (<i>Bemisia Tabaci</i>)	(Abdulridha et al., 2020b; Oh et al., 2019)
Lettuce	Root Knot Nematodes (<i>Meloidogyne spp.</i>)	(Cavalcanti et al., 2023)
	Soft Rot (<i>Pectobacterium Carotovorum</i>)	(Carmo et al., 2022)
Watermelon	Gummy Stem Blight (<i>Didymella Bryoniae</i>)	(Kalischuk et al., 2019)
	Downy Mildew (<i>Pseudoperonospora Cubensis</i>)	(Abdulridha et al., 2022)

Onion	Anthracnose (<i>Colletotrichum gloeosporioides</i> and <i>Gibberella moniliformis</i>) Stemphylium Leaf Blight (<i>Stemphylium vesicarium</i>)	(Alberto et al., 2020; McDonald et al., 2022)
Radish	Fusarium Wilt (<i>Fusarium Oxysporum</i>)	(Dang et al., 2020)
Squash	Powdery Mildew (<i>Podosphaera Xanthii</i>)	(Abdulridha et al., 2020c; Ganesh Babu and Chellaswamy, 2022)
Cabbage	Flea Beetle (<i>Psylliodes Chrysocephala</i>)	(Zhao and Shi, 2022)

The potato cultivation has been the subject of six studies, specifically: Duarte-Carvajalino et al. (2018) evaluated the severity of late blight (*Phytophthora Infestans*) in 14 different potato genotypes using multispectral images captured by drones and machine learning methods such as support vector regression, multilayer perceptron, random forest and deep learning CNN, achieving best accuracy with deep learning CNN, random forest and multilayer perceptron. This method involved the manual extraction of each subset used to train the model, which is time-consuming and can be subject to bias. On the other hand, Rodríguez et al. (2021) proposed a method that involved image segmentation through a thresholding technique, followed by the creation of training polygons, and then compared various machine learning algorithms (Fig. 10). The best results in classifying diseased plants were obtained using Linear Support Vector Classifier and Random Forest algorithms, both in terms of accuracy metrics and run time. Siebring et al. (2019) employed a different approach in the detection of symptoms caused by Erwinia bacteria and PVYNTN virus in potatoes. They used high-resolution RGB images captured by drones for detecting morphological traits of plants. Subsequently, these traits were used as input in the Random Forest model, achieving a maximum F1 score of 0.75 and an average Matthews Correlation Coefficient (MCC) score of 0.47.

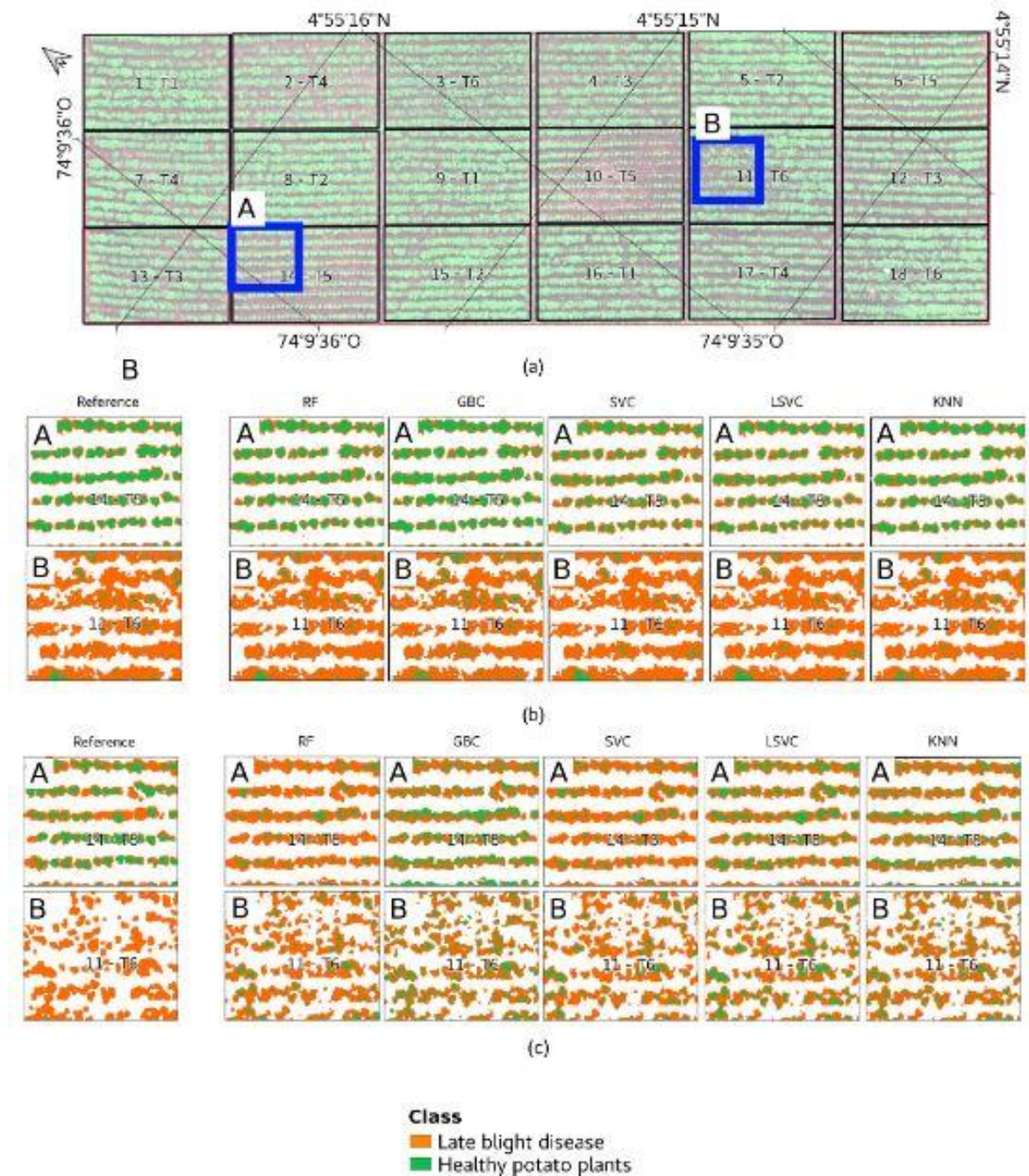


Figure 9. Classification results for two dataset (A e B) in a study on potato field. (a) overview of the study area with regions of interest depicted in blue; (b) zoom to regions of interest for dataset A showing ground reference and the classification results; (c) zoom to regions of interest for dataset B showing ground reference and classification results (Rodríguez et al., 2021).

Jindo et al. (2023) applied drones equipped with multispectral and thermal sensors to detect and estimate the effect of varying densities of *Globodera Pallida* and *G. Rostochiensis* (Cyst Nematodes) on four potato cultivars. They calculated NDVI, NDRE, weighted difference vegetation index (WDVI), and Red-Edge chlorophyll index and observed regressions with

nematode population density, finding good correlations except for one cultivar (avarna). Similar correlations were observed with thermal data.

Another important disease in potato cultivation is Verticillium wilt, which was the focus of the study by Lizarazo et al. (2023). These authors evaluated a machine learning algorithm that utilizes an ensemble of gradient boosting machines (GBMs) to differentiate between six levels of Verticillium wilt disease severity, achieving satisfactory results with F1 scores of 82% for the training dataset and 84% for the testing dataset.

Lastly, *Alternaria solani* infections were detected by Van De Vijver et al. (2022). They used a deep learning U-Net model to predict the density of lesions caused by this pathogen. Particularly, they employed ultra-high-resolution RGB images (0.3mm/px) to detect the lesions and applied a deep learning algorithm to predict their density.

Regarding tomato cultivation, several pathogens have been identified by different authors. Abdulridha et al. (2020a) detected bacterial spot and target spot both in the laboratory and in the field using hyperspectral imaging mounted on a drone,. By comparing various vegetation indices, they achieved the best results with the Photochemical Reflectance Index (PRI), NDVI₈₅₀, and chlorophyll index green (Chl_{green}). Additionally, the multilayer perceptron neural network (MLP) classification method achieved a 99% accuracy for both Bacterial Spot (BS) and Target Spot (TS).

Abdulridha et al. (2020b), in another study utilizing the same tools, also detected Tomato Yellow Leaf Curl Virus (TYLCV) in addition to BS and TS. In this study, the authors employed stepwise discriminant analysis (STDA) and the radial basis function to classify infected and healthy plants. This yielded classification rates of 98% for BS and 99-100% for TS and TYLCV diseases. The best-performing Vegetation Indices (VIs) were the renormalized difference vegetation index (RDVI) and the modified triangular vegetation index 1 (MTVI).

TYLCV was also the focus of a study by Oh et al. (2019). The authors used multi-temporal phenotypic attributes (canopy height, canopy cover, canopy volume) and VIs (NDVI, SAVI, and excess green index) extracted from UAV multispectral image data as input in an artificial neural network model. Similarly, de Oliveira Dias et al. (2023) employed ultra-high-resolution RGB images for predicting late blight severity. Random forest models were constructed, yielding determination coefficients of 0.93 (four days data) and 0.81 (one day data) in the test set.

Lettuce was the subject of two studies. Cavalcanti et al. (Cavalcanti et al., 2023) estimated the effect of root-knot nematode incidence on lettuce growth by calculating vegetation indices and Vegetation Cover (VC) from RGB images. Carmo et al. (Carmo et al., 2022) used multispectral images to detect lesions of Soft Rot (*Pectobacterium carotovorum*), employing Support Vector Machines (SVM) and Naive Bayes (NB) machine learning models.

In watermelon cultivation, Kalischuk et al. (2019) proposed a drone-assisted scouting method with multispectral cameras for Gummy Stem Blight disease, achieving early disease detection in 20% of cases. Abdulridha et al. (2022) utilized hyperspectral images to identify and classify Downy Mildew Severity Stages, achieving 62.3% accuracy for low disease severity increasing to 91% for higher severity.

In onion cultivation, Alberto et al. (2020) created geopathological maps to detect anthracnose-twister disease-infected plants using multispectral images and SVM classification, yielding 85% accuracy. McDonald et al. (2022) explored the possibility of scouting Stemphylium Leaf Blight in onions using multispectral cameras, observing differences among disease severity levels without finding correlations with various indices.

In radish cultivation, Dang et al. (2020) efficiently investigated Fusarium wilt. They segmented multispectral images captured by drones and employed a deep learning CNN algorithm for classifying diseased plants, achieving 96% accuracy.

In squash cultivation, powdery mildew was detected in two studies using hyperspectral sensors both in laboratory and field conditions. Abdulridha et al. (2020c) achieved an accuracy of 89% for asymptomatic and 96% for symptomatic phases using the Radial Basis Function (RBF). Ganesh Babu and Chellaswamy (2022) obtained 96% accuracy for the early stage and 94.2% for the final stage of disease using the Locality Preserving Discriminative Broad Learning (LPDBL).

Finally, Zhao and Shi (2022) proposed a method for detecting Flea Beetle (*Psylliodes Chrysocephala*) in cabbage cultivation using UAV RGB images. This approach, rooted in deep learning, employs an image tiling module for initial aerial image preprocessing, followed by image restoration to remove blurriness. A novel disease detection method is then introduced, enhancing CenterNet with attention and DIoU loss, resulting in superior detection performance compared to existing methods. This method achieved an overall accuracy of 87.2% AP50

(Average Precision at 50) and 94.7% R^2 for pest disease detection, meeting real-world application needs.

Water management

Water resource management plays an essential role in ensuring the quantity and quality of agricultural production, as well as adapting it to climate change and making it more sustainable (Pereira et al., 2002). In fact, especially in Mediterranean environments, there is a decreasing trend in the amount of water resources and a deterioration in their quality. In Mediterranean regions, therefore, it is crucial to adopt techniques that optimize irrigation efficiency.

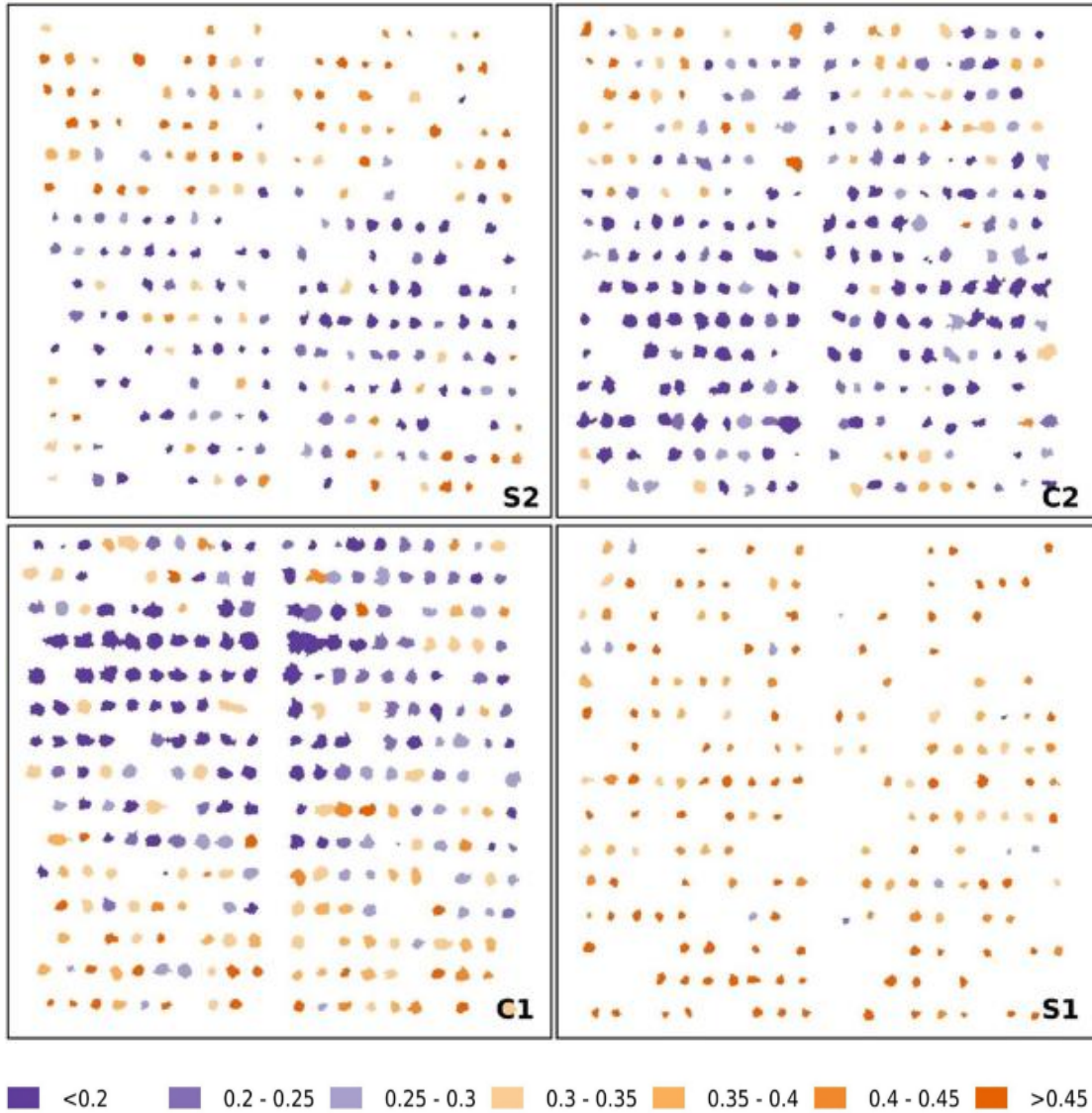


Figure 3. Maps of CWSIs values in a tomato experimental field, in salt-treated (S1 and S2) and control (C1 and C2) plots (Stutsel et al., 2021).

In this context, the use of drones is particularly advantageous. Thanks to these tools, it is possible to adopt different strategies that can improve water use efficiency. For example, optical, multispectral, and thermal sensors mounted on drones can be used to detect the crop water status (table 7).

Table 7. Overview of the different types of sensors mounted on UAVs used for different specific goals in water management.

Specific Task	Type of sensor	Crop	References
Crop water status	Thermal and RGB	Tomato	(Stutsel et al., 2021)
	Thermal and multispectral	Chili	(Coulombe et al., 2020)
		Potato	(Ekinzog et al., 2022)
	Multispectral	Tomato	(Tang et al., 2023)
		Eggplant	(Mwinuka et al., 2021)
Evapotranspiration Map	Thermal and RGB	Pepper	(Tunca et al., 2022)
	Thermal and multispectral	Potato	[156, 157]
	Multispectral	Potato	(Ebert et al., 2022)
		Tomato	[159, 162]
Soil moisture estimation	Multispectral	Potato	(Casamitjana et al., 2020)

Multispectral and thermal sensors have been used by Coulombe et al. (2020) to estimate crop water status in chili crops. Stutsel et al. (2021) determined it using RGB and thermal sensors in tomato (Fig. 11), while Mwinuka et al. (2021) used UAV-based multispectral sensors combined with handheld thermal sensors in eggplant.

Among these types of sensors, thermal sensors allow the calculation of Crop Water Stress Index (CWSI), the most well-known and widely used index for estimating water stress. Ekinzog et al. (2022) compared three CWSI models on potato cultivation (CWSIe – empirical, CWSIt – theoretical, CWSIh hybrid) for crop water stress monitoring. These indices were good predictors of soil volumetric water content (θ) ($R^2 = 0.57-0.63$), obtaining the best results with CWSIh.

Other studies have used multispectral sensors to determine crop water status. For example, in tomato, photochemical reflectance (PRI) and NDVI have allowed the estimation of stem water

potential (Tang et al., 2023). While Casamitjana et al. (2020) found the best correlations between surface soil moisture and Normalized Difference Water Index (NDWI) on potato.

Other approaches have involved the use of energy flux models that can be used to estimate irrigation water requirements by creating maps of crop evapotranspiration. Chandel et al. (2020) adopted this approach on several crops, including potato, replacing UAV-based optical and thermal data with Landsat data in an existing model. The results showed that the UAV-based data were compatible with the model, also offering greater accuracy. Tunca et al. (2022) used a two-source energy balance model (TSEB) in a bell pepper field. In this case as well, the UAV platform demonstrated great potential in mapping evapotranspiration, especially in small plots, allowing measurements at the plant level. This approach also made it possible to overcome the limitations imposed using satellites, which offer a temporal resolution of about 15 days (Ihuoma et al., 2021). Peng et al. (2023), proposed a new energy flux modelling framework based on TSEB for high spatial resolution thermal and multispectral UAV data. The results showed excellent performance of this model for retrieving evapotranspiration (ET) dynamics, confirming the reliability and precision of these tools.

Regarding the best flight modes for estimating evapotranspiration, Ebert et al. (2022) compared different flight altitudes, 30, 60, and 90 meters above ground, obtaining that there are no advantages to flying at low altitudes, confirming the validity of surveys conducted even at 90 meters.

Finally, another strategy for UAV-based water management is the one adopted by Rozenstein et al. (2023) in a study conducted on tomato. UAV-captured multispectral images were used to estimate evapotranspiration by calculating the FAO-56 crop coefficient (K_c). Results show that this method estimated evapotranspiration to derive the irrigation dose in near-perfect agreement with best-practice irrigation, both in terms of total amount and irrigation rate.

Yield and biomass estimation

In the case of vegetable crops, the early prediction of crop productivity and quality is an important factor that allows for the best possible planning of harvesting, storage, shipping, and sales operations. This estimate is currently carried out manually, which is time-consuming and often approximate and inaccurate. The use of drones for this purpose can be a good solution, as it is one of the most established and widespread applications in agricultural crops in the

scientific community (Y. Chen et al., 2019). In fact, drones can be used to predict yield in terms of both fruit production and biomass of multiple vegetables species. Researchers have adopted various techniques and used different types of sensors to arrive at a precise and geospatialized estimation of the yield. As shown in table 8, one of the determining factors in the choice of approach to be used for this purpose is the crop habitat.

Table 8. Summary of the different yield estimation approaches in various crops.

Approach	Type of Yield predicted	Species	Reference
Object Detection	Fruit yield	Pumpkin	(Midtby and Pastucha, 2022; Wittstruck et al., 2021)
		Strawberry	(Y. Chen et al., 2019)
		Yellow melon	(Kalantar et al., 2020)
	Maturity level of fruit	Strawberry	(Zhou et al., 2021)
		Cauliflower	(Psiroukis et al., 2022)
	Stem density variation	Potato	(Mhango et al., 2022)
Predicted model based on shape features	Fresh matter	Eggplant, Tomato and Cabbage	(Astor et al., 2020)
	Seed Yield	Spinach	(Ariza-Sentís et al., 2023)
	Biomass and Yield	Tomato	(K. Johansen et al., 2019)
Predicted model based on Vegetation Indices	Dry-Biomass	Leek	(Haumont et al., 2022)
	Tubers Yield	Potato	(Jasim et al., 2020)
	Fruit yield	Strawberry	(Oliveira et al., 2023)
Multi-Source Prediction model	Fruit yield	Pepper	(Tunca and Köksal, 2022)
		Tomato	(Ashapure et al., 2019; Chang et al., 2021; Lillo-Saavedra et al., 2022)
	Fresh and dry biomass	Spinach	(Awika et al., 2021)
	Biomass and Yield	Tomato	(Tatsumi et al., 2021)

In studies conducted on crops where the productive organs were exposed and visible from aerial images, one of the strategies found was fruit detection. Using RGB sensors and object detection and counting techniques, several authors have identified and quantified the production of strawberry (Y. Chen et al., 2019), yellow melon (Fig.12) (Kalantar et al., 2020) and pumpkin (Midtiby and Pastucha, 2022; Wittstruck et al., 2021).

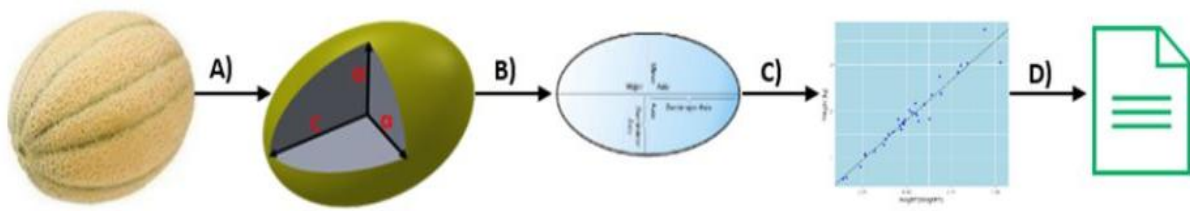


Figure 4. Yield estimation process. Stage (A) melon by spheroid shape using pre-knowledge of melon shape, (B) conversion from 3D to 2D, (C) linear regression for yield prediction, (D) report for each melon location and yield estimation for the field (Kalantar et al., 2020).

Other strategies involved the use of machine learning algorithms based on UAV multispectral data. Oliveira et al. (2023) used the support vector machine (SVM) and linear regression (LR) models on strawberries, with the latter obtaining better yield estimates. In particular, the LR model obtained 99.91% accuracy for the average fruit weight, 99.55% for the number of fruits, and 99.94% for the number of leaves. UAV-RGB data were instead used by Johansen et al. (2019) to estimate tomato yield. For this purpose, the authors used shape features such as plant area, border length, width, and length as input to random forest models, obtaining R^2 values against fresh shoot mass, yield mass, and fruit numbers as high as 0.67, 0.44, and 0.41, respectively.

Furthermore, several authors have employed multi-source models. These models consider both geometric characteristics such as canopy cover, canopy height, and canopy volume, as well as spectral characteristics, through the calculation of vegetation indices. This approach has been adopted by several authors (Ashapure et al., 2019; Chang et al., 2021; Lillo-Saavedra et al., 2022; Tatsumi et al., 2021) in tomato cultivation and by Tunca and Köksal (2022) in pepper cultivation. This method has proven to be an effective strategy in providing the authors with more accurate and reliable predictions.

In crops where production is below the soil surface, productivity estimation is indirect, leading to various strategies. For example, in potato cultivation, Jasim et al. (2020) found good correlations between yield and vegetation indices derived from multispectral images. Mhango et al. (2022) used a deep convolutional neural network (CNN) for the identification and estimation of stem density, a parameter that strongly characterizes potato yield.

Additionally, in leafy vegetables, the parameter that represents productivity is biomass. This has been successfully estimated in cabbage by Astor et al. (2020) through information on crop height derived from point clouds based on UAV RGB data. Haumont et al. (2022) used UAV multispectral imaging for the estimation of dry biomass in leek, obtaining correlations up to $R^2=0.90$. Awika et al. (2021) estimated spinach biomass through a predictive model that takes as input geometric information (plant height, canopy coverage, and volume) and spectral characteristics (excess greenness index (ExG), chlorophyll red-edge (Chl_{RE}), normalized difference vegetation index (NDVI) and normalized difference red-edge (NDRE)). Even in spinach cultivation, Ariza-Sentís et al. (2023) adopted an approach for spinach seed yield estimation for seed production purposes, which consists in correlating the number of plants and two phenotyping variables (plant area and canopy cover percentage) with the number of harvested seeds and the thousand seed weight. The results showed a high linear correlation R^2_{adj} of 0.80.

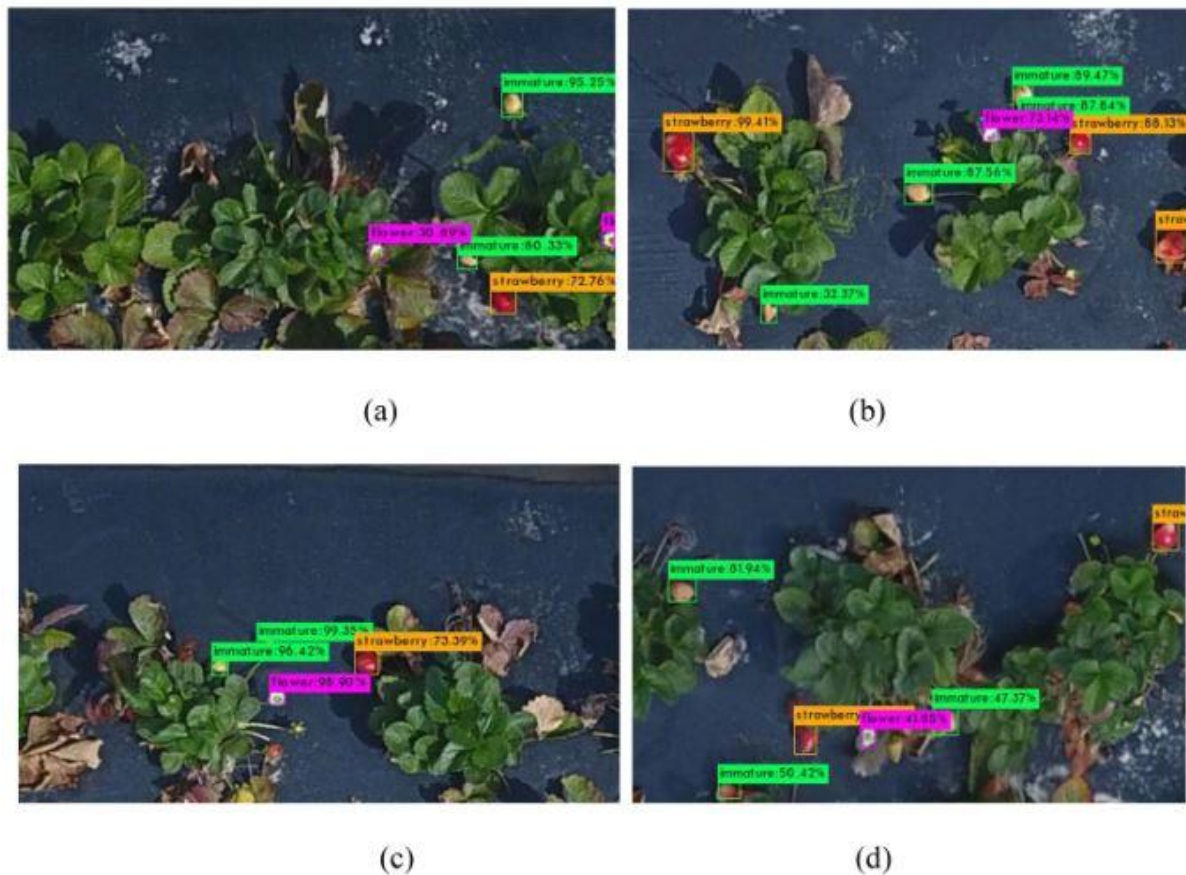


Figure 5. Strawberry maturity detection and classification results using YOLOv3 from UAV images (Zhou et al., 2021).

Beyond quantitative yield estimation, some authors have conducted studies on maturity level classification. This was performed on broccoli, where Psiroukis et al. (2022) employed object-based image analysis (OBIA) techniques to classify different maturity levels based on geometric characteristics of the head. For strawberries, Zhou et al. (2021) identified and classified various maturity levels using YOLO v3, a Deep Learning algorithm (Fig. 13). The results showed that three strawberry maturity stages were classified with a mean average precision (mAP) of 0.88, and 0.93 for fully mature fruit.

Aerial spraying

The use of drones on vegetable crops for spraying operations has been investigated in recent studies by several authors. Drones equipped with a spraying system capable of performing targeted aerial treatments, leading to significant input savings, are used. The main components of aerial spraying drones include Brushless Direct Current Motors (BLDC), Electronic Speed

Control (ESC), flight controller, GNSS system, accelerometer, gyroscope camera, transmitter, and receiver. For spraying, the two primary components are the pump and its controlling system (Fig. 14) (Hafeez et al., 2023).



Figure 6. UAV based spraying system used in different crops (Hafeez et al., 2023).

The use of drones for spraying is becoming increasingly widespread, being a highly valuable equipment for farmers and attracting attention in the scientific community as well. In the field of vegetable crops, three notable studies have explored the applications of pesticides, fertilizers, and defoliants using UAV-sprayers. In particular, Xiao et al. conducted a study in 2020 aiming to compare droplet deposition and control efficiency between UAV and electric air-pressure knapsack (EAP) sprayers on a pepper field. Despite UAV gave lower droplet coverage, density, and uniformity in deposition, it achieved greater deposition at $1.01 \mu\text{g}/\text{cm}^2$, which was 98% higher compared to that obtained with the EAP sprayer. This allowed for effective control of aphids and *Phytophthora capsici*.

Another study was carried out by Jingxin et al. (2021) on fertilizer applications in pumpkins aiming to evaluate the effect of working parameters on droplet deposition. Operating the drone at a flight height of 2.5 m and a speed of 3 m/s resulted in maximal droplet deposition and a high level of attachment on the backside of the leaves. Lastly, in the case of defoliant spraying, Yapeng Liu et al. (2022) assessed the effect of aerial adjuvants on droplet deposition on pepper plants. The most favourable outcomes were achieved employing the adjuvant "Puliwang" underscoring that specific adjuncts within such applications can substantially amplify droplet deposition and defoliation rate, thus augmenting treatment efficiency significantly.

These first results indicate the potential of UAVs in safeguarding and managing vegetable crops. Drones offer an innovative and valuable tool for optimizing agricultural treatments.

Discussions

The use of drones on vegetable crops has emerged as a growing research area in recent years. This review focuses on analysing the different applications of drones and the opportunities these devices offer to farmers and researchers for optimizing vegetable crops management.

Crop detection through drones represents the fundamental initial step to conduct further analyses of agricultural plots. By employing various types of UAV-based sensors, it is possible to identify the target crop, referred to as the Region of Interest (ROI), and isolate it (Ye et al., 2023). This approach provides a detailed view of the crop and excludes its surroundings, facilitating rapid and efficient mapping of the different crops present in the field. The same types of sensors and methods used for crop detection, both pixel-based and object-based, also allow for the identification and mapping of weeds, where the ROI is the weeds. This process lays the foundation for site-specific weed management (SSWM) (Ajayi et al., 2023).

Moreover, crop detection enables further operations such as extracting morphological and geometrical plant characteristics from images captured by drones. Photogrammetry techniques enable the extraction of key parameters such as Leaf Area Index (LAI), plant height, volume, and biomass (Lee et al., 2023). This information supports an efficient phenotyping process, benefiting not only farmers but also breeders (Antonucci et al., 2023).

Monitoring plant health and stress has been the most prevalent application observed in this review. Many authors have employed parameters calculated from high-resolution aerial images to assess treatment efficacy (Garcia-Garcia et al., 2021), confirming that these tools are now firmly established and reliable for evaluating variations in plant vigor, overall well-being, and stress in space and time. Additionally, researchers have developed specific indices and methods to generate maps of nitrogen and chlorophyll content (Angel and McCabe, 2022; Fan et al., 2023b).

Another application domain of drones is the detection of diseases and pests through remote sensing. Although still evolving, the analysed papers demonstrate that drones equipped with hyperspectral, multispectral, and in some cases, RGB sensors are efficient and reliable tools for scouting symptoms induced by pests and diseases (Dang et al., 2020). Conversely, identifying diseases during asymptomatic stages and accurately classifying various levels of symptom severity is a continually growing field (Abdulridha et al., 2020c).

Water management is crucial for proper crop management and holds significant environmental and economic relevance. Drones equipped with both thermal and RGB/multispectral sensors can make substantial contributions to water resource management. They can calculate water stress indices, estimate evapotranspiration, and determine crop coefficients (kc), enabling precise irrigation planning and optimal water resource utilization (Ekinzog et al., 2022; Rozenstein et al., 2023; Tang et al., 2023).

All types of crops, including vegetables, experience an annual cycle that reaches its culmination with the harvesting phase. Drones can be useful decision support tool at this stage, as they can provide early, detailed, and geospatialized yield estimates through their utilization. This application has garnered considerable scientific interest in recent years and has found practical implementation in the agricultural sector, affording farmers the ability to plan harvesting, transportation, storage, and sales operations (Lillo-Saavedra et al., 2022; Midtiby and Pastucha, 2022). However, accurately estimating ripeness levels and classifying various levels of maturity present in the field could be a future research opportunity. Two authors have examined this aspect, respectively in strawberries and broccoli, reaching excellent results and inspiring potential applications in other crops (Psiroukis et al., 2022; Zhou et al., 2021).

The previously mentioned applications have demonstrated how drones, equipped with cameras and sensors, can efficiently monitor crops from their initial emergence to harvest. Moreover, these vehicles offer the capability to conduct various operations. One of the most innovative uses in this regard is aerial spraying. Drones deployed for this purpose are appropriately sized and equipped with various types of spraying systems. These technologies have been tested on vegetable crops in three studies involving applications of pesticides, fungicides, defoliant, and fertilizers (Jingxin et al., 2021; Yapeng Liu et al., 2022; Xiao et al., 2020). The results of these applications are the basis for further research.

Conclusions

The review points out the significance of drone applications in vegetable crops and the immense potential of these tools in enhancing cultivation efficiency. Drone applications in vegetable crops in the literature are increasing more and more, with the number of dedicated papers on this subject growing year by year.

The scientific knowledge in this field, combined with the array of information that drones can provide, will be employed by agronomists, agrotechnicians, and specialized consultants in precision agriculture. These professionals will be capable of offering farmers increasingly informed and precise operational guidance, thereby contributing to the optimization of agricultural management practices and yielding economic and environmental benefits.

From an economic standpoint, drones can provide a dual advantage. Their utilization enables the reduction of input quantities such as herbicides, fertilizers, pesticides, and water but also the prevention of damages through early diagnosis of various stress types. Additionally, input savings can yield environmental benefits, positioning these technologies as potential solutions for the environmental sustainability of vegetable crops (Butte et al., 2021; Khan et al., 2021a).

However, it is imperative to continue research and development to face technological challenges and make these tools increasingly accessible and effective for the agricultural sector where tradition is strong, and innovations are gradually accepted and adopted.

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Section 3. Crop health and stress monitoring

Spatiotemporal variability of nitrogen nutrition index in potato fields: a UAV-based machine learning approach using a bayesian critical nitrogen dilution curve

Abstract

Nitrogen (N) management is one of the main factors enhancing potato productivity and promoting sustainable agricultural practices. The Nitrogen Nutrition Index (NNI, obtained as the ratio of actual plant N, to the critical plant N concentration) is widely applied to assess the N status of various crops. Traditionally, NNI is calculated using field data, but remote sensing (RS) technologies can offer more rapidly and timely assessment of the spatiotemporal (within field) variability of this index.

This study employs multispectral data acquired via Unmanned Aerial Vehicle (UAV) and machine learning (ML) models to estimate potato NNI. A Bayesian hierarchical partially pooled method was applied to a three-year field experiment in Denmark, together with extensive ground-based potato datasets, to model the critical nitrogen dilution curve (CNDC) and calculate the NNI.

Multispectral UAV data were processed to extract four spectral bands and calculate several vegetation indices, which were used as predictors to train and test six ML models: Linear regression, support vector machines, gaussian process regression, stepwise linear regression, ensemble trees and neural networks.

Among the compared models, gaussian process regression model outperformed the others, showing R^2 equal to 0.83 and a RMSE of 0.10 and providing accurate NNI predictions, comparable to ground-based Bayesian estimates. The variability of the NNI was analyzed over the seasons using 28 NNI maps derived from UAV surveys at spatial resolution of 0.04–0.09

m/pixel, capturing spatial variations in crop N status over time. The proposed framework, designed for NNI prediction at the intra-field scale, has the potential to be adapted to different environments and crops.

The framework can support practical decisions for precision N management, reducing the environmental impact of potato cultivations and enhancing sustainability.

Keywords: Precision Agriculture, UAV, Crop Nitrogen Management, Gaussian Process Regression.

Supplementary materials, including additional figures and tables, are provided at the end of this chapter.

Introduction

Nitrogen (N) fertilization is one of the most important agricultural management practices, but it is highly complex as it needs to be managed in space and time, as N has a very strong impact on crop performance and environmental sustainability. In potato production, optimized N management can indeed provide a boost to yields alongside reducing widespread environmental pollution caused by excess N, for example, through emissions and leaching (Giletto et al., 2019; Ziadi et al., 2012). Therefore, scientific research continues to focus on developing new approaches, theories and tools to further optimise N use (Berger et al., 2020; Goffart et al., 2023).

Remote Sensing (RS), along with other tools, is one of the most powerful methods for helping screening the spatial and temporal variability of crop growth status (Castilho et al., 2024; Lapaz Oliveira et al., 2023). The use of RS techniques enables the screening of key plant characteristics (i.e. geometric and spectral) that are informative about the crop N status (Fan et al., 2023a; Morier et al., 2015; Tang et al., 2024). The use of RS in agriculture has increased during the last decade, spurred by advances in Unmanned Aerial Vehicles (UAVs) (Canicatti and Vallone, 2024; Roma et al., 2025) and the integration of machine learning (ML) algorithms and artificial intelligence (AI) (Canicatti et al., 2025c; Li et al., 2024, 2023; H. Yang et al., 2023). Today, RS-based N recommendations and screening combined with ML and AI extends across the range of crops, from cereals to horticultural crops and to pasture (Camarano et al., 2011; Khose and Mailapalli, 2024; Patel et al., 2021; Zheng et al., 2018).

The use of novel RS approaches can assist on screening for changes in the canopy N status, which can also be estimated with the Nitrogen Nutrition Index (NNI) (Zhou et al., 2025). The

NNI is defined as the ratio between the N concentration of the plant in a certain growth stage, %N, and the critical N concentration (N_c), defined as the minimum plant N concentration required to achieve maximum crop growth rate. This N_c is determined by the critical nitrogen dilution curve (CNDC), which describes the allometric relationship of the plant %N, decreasing with increasing plant biomass. Thus, for any given crop biomass, there is an assigned N_c below which growth rate will be reduced (Lemaire and Gastal, 1997).

Usually, an NNI value greater than 1 indicates N luxury, an NNI close to 1 denotes an optimal N status, while an NNI less than 1 indicates N deficiency. This index has been used for the assessment of crop N status in many herbaceous crops (Ciampitti et al., 2022; Ye et al., 2024) and as a surrogate for agronomic and environmental parameters (e.g. N use efficiency (NUE), radiation use efficiency (RUE) and yield prediction) (Bohman et al., 2021; Giletto and Echeverría, 2012; Hu et al., 2014; Rodriguez et al., 2024). Potato specific CNDCs were developed across various regions, considering local cultivars and environmental contexts (Soratto et al., 2022). For instance, (Giletto and Echeverría, 2012) developed a CNDC valid for the pampas of Argentina, which is different from those previously reported in Canada (Bélanger et al., 2001).

Traditionally, crop NNI is determined via destructive sampling to measure dry matter (DM) and %N. Although some studies have developed curves based solely on shoot or root biomass, the most common measures include both above-ground and root components of the plant, resulting in laborious and time-consuming process (Chakwizira et al., 2016; Giletto et al., 2020). Moreover, destructive sampling methods provide information limited only to specific sampling points. This restricts the ability to capture the spatial variability across fields and severely limits the temporal frequency of data acquisition, thereby hindering a comprehensive assessment of crop N status dynamics (Dong et al., 2024).

NNI calculation (i.e. with statistical model) has also evolved from more traditional (Fernandez et al., 2022; Justes et al., 1994) to simplistic approaches (Abdallah et al., 2016) to the more sophisticated Bayesian methods. Actually CNDCs can be estimated through various statistical methods, each potentially leading to differences in parameter estimation and accuracy (Li et al., 2022). Traditional frequentist methods, which commonly rely on maximum likelihood estimation, are particularly vulnerable to biased or limited datasets, often resulting in unreliable parameter estimates due to small-sample bias and neglect of parameter uncertainty. In contrast, hierarchical Bayesian approaches have been shown to address these shortcomings effectively.

For example, Lacasa et al. (2023) demonstrated that the hierarchical Bayesian framework outperforms conventional sequential methods, especially when datasets are small or biased. The Bayesian approach explicitly incorporates uncertainty in parameter estimation, providing more robust and reliable CNDC estimations under challenging data conditions. The Bayesian framework, originally provided by Makowski et al. (2020), can be applied on data without N-limited classifications, enabling also the quantification of uncertainty of CNDC results. This approach was adopted on wheat by Yao et al. (2021), while Ciampitti et al. (2021a) extended it to maize, examining CNDC variation across genotype, environment, and management. Bohman et al. (2023) adapted this model for potatoes, employing partial pooling for the estimation of variation in α and β parameters globally, where α and β represent the empirical fitted parameters of the CNDC. This model provided robust results even when the data were limited; it produced reliable estimates of the parameters with measures of uncertainty (Bohman et al., 2023; Yao et al., 2021).

The critical phase to select an appropriate CNDC for accurate NNI determination, coupled with the complex nature of destructive sampling methods, has driven the development of non-destructive approaches for direct NNI estimation (Song et al., 2022).

The use of spectrometers to estimate NNI from the reflectance in specific spectral bands was studied by Liu et al. (2020) and Zhao et al. (2018). These studies documented that green, red edge, near-infrared (NIR) bands and derived vegetation indices (VIs) are sensitive to changes in N crop status in both maize and winter wheat cultivations. In other studies, digital cameras were used to quantify canopy cover as parameter for building a CNCD based on images (Wang et al., 2016). UAV has been also used to directly estimate NNI; on wheat, for example, UAV-based data with ML algorithms, have shown great potential in enhancing the accuracy of NNI estimation (Jiang et al., 2023; Zhang et al., 2024). Qiu also found positive results in using UAVs in rice, estimating NNI using RGB cameras coupled with ML models (Qiu et al., 2021). Meanwhile, similar results have been reported for maize (Liang et al., 2023), oilseed rape (Liu et al., 2018), and grass seed crops (Wang et al., 2019). One example is represented by Pereira's study, where UAV-based data combined with ML were used for N variability assessment in pasture fields; in that case, the high spatial resolution of these systems outperformed other RS platforms (Pereira et al., 2022). Applications and example of such kind on potatoes are scarce; one is the work conducted by Peng et al. (2021), where RS-based N status estimations over

potatoes showed that UAV increased precision and robustness for key parameter estimation, like N requirement, NUE, and NNI, against satellite imagery, which has a coarser resolution.

Among these studies, the process to derive CNDC for NNI calculation used to train ML models is often vague or rely on old curves, lacking flexibility in adapting to changing environmental conditions or crops. Indeed, the choice of the curve may lead to significant variation of NNI. One approach that integrates strong models for NNI determination, while being adaptable to changes in environment and crop, would lead to more robust and versatile tools across a wide range of environments and cropping systems.

To fill this gap, this study aims to build a robust methodological framework for quantifying within-field spatiotemporal variability of the NNI in potato cultivation. The underlying hypothesis is that the proposed UAV-based framework enables accurate detection and quantification of spatial and temporal variations in crop N status through non-destructive methods. Therefore, the objectives of this study are: i) to calculate the NNI on potato by using a partially-pooled Bayesian hierarchical method; ii) to compare ML algorithms' ability to estimate NNI; and iii) to assess the spatial and temporal variability of NNI in a potato field in Denmark.

Materials and methods

Site description

The field experiments were conducted in the region of Central Denmark, at the Department of Agroecology, Aarhus University Viborg (56° 31' 41"N, 9° 24' 53"E) (WGS 84, EPSG: 4326) (Fig. 1). This area was characterized by a temperate Atlantic climate, with an average annual temperature of about 10°C and a summer temperature of 18°C. Day length varied from 7 hours in winter to 17 hours in summer, with a total of approximately 1,600 hours of sunlight per year. The annual rainfall was around 800 mm, evenly distributed, with a slight prevalence in autumn and winter. Field experiments were conducted between 2017 and 2019 (three growing seasons) on coarse sandy soil, consisting of 3.9% clay, 2.3% silt, 92% sand, with an organic carbon content of 1.34% and a pH of around 6 (Peng et al., 2021).

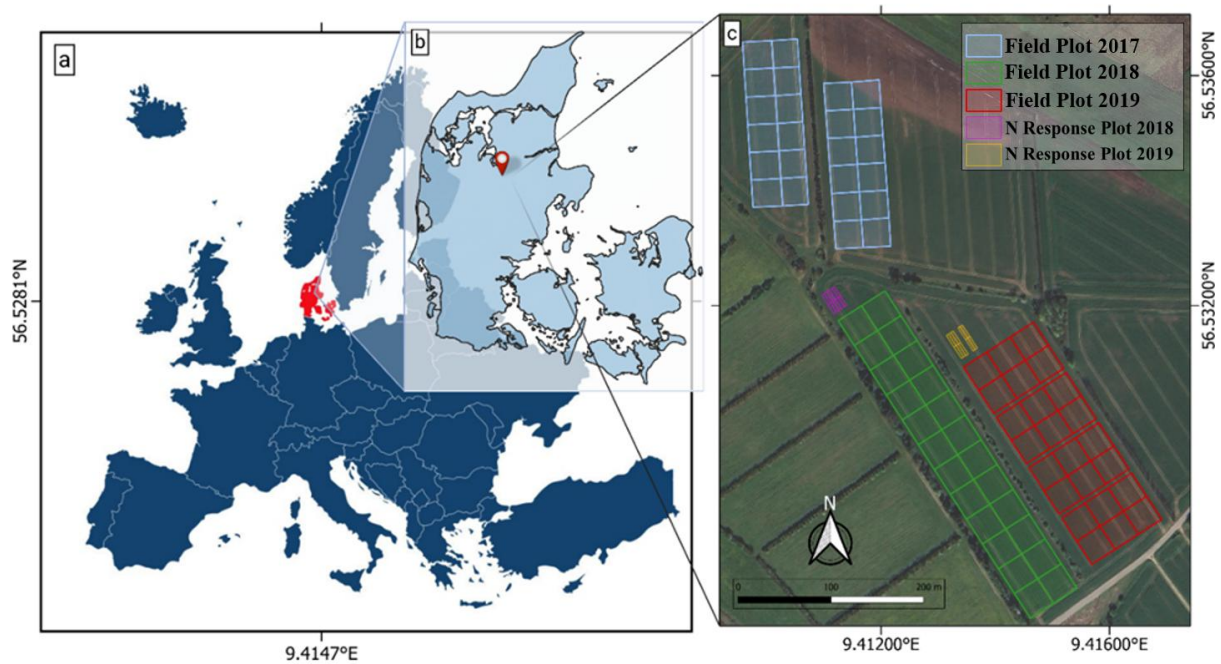


Fig. 1. Experimental field location (56.5281° N; 9.4147° E) (a-b), and trials setup for the 2017 (blue squares), 2018 (green squares), and 2019 (red squares) growing season (c). The violet and yellow squares represent the nitrogen (N) response plots for the growing seasons 2018 (violet squares) and 2019 (yellow squares), respectively.

Every growing season, adjacent fields were used, with a total area of 2.85 ha in 2017, 2.61 ha in 2018, and 2.58 ha in 2019 (Fig. 1). The cultivated crop was potato (*Solanum tuberosum* L.), variety Oleva. The potato was transplanted in the first days of May, with a spacing of 0.85 m between rows and 0.35 m between plants. The plots, with 24 × 24 m net dimensions, were arranged according to a randomized block design with a split-plot treatment replicated four times (Fig. 1). The main treatment was irrigation (Tab. 1), divided into three levels: minimal (I0), optimized (I1) and full (I2) determined based on soil moisture, which was measured by time domain reflectometers down to a depth of 0.60 m (for details on quantities, see Tab. 1a). The secondary treatment was N fertilization (Tab. 1a), with two levels: full (N2), in line with Danish agricultural regulations, and optimized (N1), with split applications based on the approach defined by (Zhou et al., 2017). Approximately 65 kg of N per hectare were applied before transplanting in all the field, primarily in the form of organic pig manure. N mineralization, derived from soil organic matter, was expected to contribute with about 45 kg of N per hectare (Manevski et al., 2015). After transplanting, potassium (K), phosphorus (P), magnesium (Mg) and sulfur (S) were added following standard practices. For N2 fertilization 140-150 kg N/ha were also applied in this phase (12 days after emergence, DAE); for N1 80-

120 kg N/ha were applied in multiple doses during the season. Fertilization timing depended on the growing season. In 2017, it was carried out on June 30 (DAE 32) and July 17 (DAE 49), with an additional dose for I1 fields on July 28 (DAE 60). In 2018, fertilization was made on August 2 (DAE 72), while in 2019 it occurred on July 18 (DAE 45) and August 7 (DAE 65). Plant and tuber sampling was carried out in mid-season.

Tab. 1 Irrigation and N fertilization management across different treatments. Soil organic matter mineralization, estimated to contribute approximately 45 kg of N per hectare, is not included in the table (Manevski et al., 2015).

(a) Field	Year	I0 N1	I0 N2	I1 N1	I1 N2	I2 N1	I2 N2
Irrigation water (mm)	2017	10	10	60	50	65	65
	2018	14	12	161	146	208	205
	2019	30	30	102	103	154	154
N fertilizer (kg N/ha)	2017	166/206*	236	166	236	166	236
	2018	116	196	156	196	156	196
	2019	136	196	136	196	136	196
(b) N Response Plot	Year	N 0	N 60	N 140	N 200	N 240	
Irrigation water (mm)	2018	165	165	165	165	165	
	2019	152	152	152	152	152	
N fertilizer (kg N/ha)	2018	0	60	140	200	240	
	2019	0	60	140	200	240	

* Two plots received different doses of N fertilizer, according to the methodology by (Zhou et al., 2017).

In addition to the main experimental fields, supplementary fields were cultivated in 2018 and 2019 to evaluate crop response to different N levels. They covered an area of 0.042 ha in 2018 and 0.045 ha in 2019. Within this area, 10 response plots were set up using a randomized block design with a split-plot treatment structure, each replicated twice.

In 2018, each plot measured 3.5×12 m, while in 2019, the dimensions were 3×15 m. The treatment was N fertilization, with five different application rates: 0, 60, 140, 200, and 260 kg N/ha. All plots were fully irrigated throughout the growing season (see quantities on Tab. 1b).

Plant sampling, measurements, and N determination in the plant tissues

Each growing season, potato's plants were mid-season sampled, during flowering, which corresponds to BBCH stages 65–70. The number of DAE was 65 in 2017, 63 in 2018, and 56 in 2019. The harvest for above-ground biomass and tubers was made at BBCH stages 95–96, with DAE 106 in 2017, 113 in 2018, and 105 in 2019. The total tuber harvest took place a few weeks later. In each plot, mid-season sampling was carried out in areas of 1.40×1.70 m. For the harvest, foliage was collected from an area of 1.75×1.70 m, while tubers were collected from an area of 10×3.40 m. Foliage was collected near to the area where the mid-season sampling took place, while tubers were harvested from the opposite side of the centre of the plot. Samples were stored at 4°C before measuring fresh weight and then dried in an oven at 60°C for 48 hours to determine DM. The dried samples were ground and analyzed to determine %N using the Dumas method (Elementar Analysensysteme GmbH, Germany). Growth stages and plant conditions were monitored from emergence until harvest, which took place in the first week of November.

UAV data collection

During the growing season, multispectral data were collected using drones under stable radiation conditions, between 10:00 AM and 2:00 PM. In 2017, a fixed-wing eBee drone (Parrot Group, Switzerland) equipped with a SenseFly multiSPEC 4C (Parrot Group, Switzerland) multispectral camera was used. This camera captures green (550 nm), red (660 nm), red-edge (735 nm) and NIR (790 nm) bands. In 2018 and 2019, a DJI Matrice 100 quadcopter (DJI, China) equipped with a Micasense RedEdge multispectral camera (Micasense, Seattle, USA) was used, measuring blue (475 nm), green (560 nm), red (668 nm), NIR (840 nm), and red-edge (717 nm) bands. UAV flights were performed at varying altitudes (approximately 60–100 m) and speeds (3.5–5.5 m/s), yielding ground sampling distances (GSD) between 0.04 and 0.09 m/pixel (See full details in Tab. 2). For georeferencing, four to six ground control points (GCP) were set up, evenly distributed on the field boundaries, with data collected using a Trimble RTK GPS (Trimble Inc., USA). Additionally, camera calibration panels were scanned before and after each flight to ensure radiometric calibration.

Tab. 2 Summary of Unmanned Aerial Vehicles (UAV) data collected in this study.

Year	Sensor used	Spectral bands aquired	Flight N°	DOY*	Flight altitude (m)	GSD** (m/pixel)	Digitization Footprint (Mb/ha)
2017	SenseFly multiSPEC 4C	Green, Red, Red-Edge, NIR	1	194	88	0.10	8.53
			2	200	75	0.08	12.01
			3	235	79	0.08	10.85
2018	Micasense RedEdge multispectral	Blue, Green, Red, Red-Edge, NIR	1	131	82	0.05	26.91
			2	151	107	0.07	15.92
			3	158	105	0.07	16.46
			4	173	82	0.05	26.99
			5	180	83	0.05	26.30
			6	185	83	0.05	26.10
			7	192	86	0.06	24.54
			8	200	85	0.06	25.29
			9	205	63	0.04	46.09
			10	213	62	0.04	47.26
			11	220	85	0.06	25.11
			12	228	85	0.06	25.03
			13	233	83	0.05	26.30
			14	243	62	0.04	47.95
			15	245	61	0.04	49.38
			16	248	61	0.04	48.39
2019	Micasense RedEdge multispectral	Blue, Green, Red, Red-Edge, NIR	1	151	102	0.07	17.35
			2	157	111	0.07	14.73
			3	178	104	0.07	16.88
			4	186	105	0.07	16.49
			5	191	104	0.07	16.94
			6	199	106	0.07	16.19
			7	207	111	0.07	14.76
			8	226	105	0.07	16.62
			9	261	166	0.11	6.57

*DOY= Day of Year; **GSD = Ground sampling distances.

After data collection, the multispectral data were processed using Pix4Dmapper software (version 4.2.27 (“Pix4Dmapper: Professional Photogrammetry Software for Drone Mapping,” n.d.)). The downloaded images were orthorectified and aligned to ensure geometric accuracy, and a 3D point cloud was generated from them. An orthomosaic was then created for the different bands: red, green, blue, NIR, and red-edge. The images were further processed using QGIS (QGIS Development Team, 2023) and Python software (Python Software Foundation, 2023). A regular sampling grid was implemented within each plot to ensure the accurate

extraction of spectral features while minimizing contamination effect caused by adjacent plots and the tractor trajectory, central to each plot. Specifically, four 5×5 m subplots were delineated within each 24×24 m plot, which allowed for a representative evaluation of the spectral features used to train the ML models. For each sampling date, the values related to the spectral bands were extracted using the function *zonal_stats* from the *rasterstats* Python library. Additionally, various VIs were calculated, selected based on scientific literature and the available bands. The calculated indices are reported in Tab. 3.

Tab. 3 Summary of Vegetation Indices (VIs) used in this study.

Index	Long Name	Equations	References
NDVI	Normalized		
	Difference	$\frac{\rho \text{ NIR} - \rho \text{ RED}}{\rho \text{ NIR} + \rho \text{ RED}}$	(J. W. Rouse et al., 1974)
	Vegetation Index		
GNDVI	Green Normalized		
	Difference	$\frac{\rho \text{ NIR} - \rho \text{ GREEN}}{\rho \text{ NIR} + \rho \text{ GREEN}}$	(BUSCHMANN and NAGEL, 1993)
	Vegetation Index		
NDRE	Normalized	$(\rho \text{ NIR} - \rho \text{ RED EDGE}) /$	
	Difference Red Edge	$(\rho \text{ NIR} + \rho \text{ RED EDGE})$	(Ustuner et al., 2014)
Cl _{rededge}	Chlorophyll Index red edge	$\left(\frac{\rho \text{ NIR}}{\rho \text{ RED EDGE}} \right) - 1$	(Gitelson et al., 2003)
CVI	Chlorophyll vegetation index	$\frac{\rho \text{ NIR} * \rho \text{ RED}}{\rho \text{ GREEN} * \rho \text{ GREEN}}$	(Vincini et al., 2007)
MCARI	Modified	$((\rho \text{ RED EDGE} - \rho \text{ RED}) -$	
	Chlorophyll	$0.2 * (\rho \text{ RED EDGE} -$	
	Adsorption Ratio Index	$\rho \text{ GREEN})) * (\rho \text{ RED EDGE} / \rho \text{ RED})$	(Daughtry et al., 2000)
NDI	Normalized		
	Difference Index	$\rho \text{ NIR} - \rho \text{ RED}$	(Birth and McVey, 1968)
RVI	Simple Ratio Index	$\frac{\rho \text{ NIR}}{\rho \text{ RED}}$	(Birth and McVey, 1968)
OSAVI	Optimized Soil		
	Adjusted Vegetation Index	$\frac{1.16 * (\rho \text{ NIR} - \rho \text{ RED})}{(\rho \text{ NIR} + \rho \text{ RED}) + 0.16}$	(Rondeaux et al., 1996)
SAVI	Soil Adjusted		
	Vegetation Index	$\frac{1.05 * (\rho \text{ NIR} - \rho \text{ RED})}{(\rho \text{ NIR} + \rho \text{ RED}) + 0.5}$	(Huete, 1988)
EVI2	Enhanced Vegetation		
	Index 2	$\frac{2.5 * (\rho \text{ NIR} - \rho \text{ RED})}{(\rho \text{ NIR} + 2.4 * \rho \text{ RED} + 1)}$	(Jiang et al., 2008)
MSR	Modified Simple	$\frac{\rho \text{ NIR}}{(\rho \text{ RED} - 1)}$	
	Ratio	$\left(\sqrt{\frac{\rho \text{ NIR}}{\rho \text{ RED}}} \right) + 1$	(Chen, 1996)

WDRVI	Wide Dynamic Range Vegetation Index	$\frac{(0.1 * \rho \text{ NIR} - \rho \text{ RED})}{(0.1 * \rho \text{ NIR} + \rho \text{ RED})}$	(Gitelson, 2004)
MTCI	MERIS Terrestrial Chlorophyll Index	$\frac{\rho \text{ NIR} - \rho \text{ RED EDGE}}{\rho \text{ RED EDGE} - \rho \text{ RED}}$	(Dash and Curran, 2004)
NLI	Nonlinear Index	$\frac{\rho \text{ NIR}^2 - \rho \text{ RED}}{\rho \text{ NIR}^2 + \rho \text{ RED}}$	(Goel and Qin, 1994)
RDVI	Renormalized Difference Vegetation Index	$\frac{\rho \text{ NIR} - \rho \text{ RED}}{\sqrt{\rho \text{ NIR} + \rho \text{ RED}}}$	(Roujean and Breon, 1995)
GRVI	Green Red Vegetation Index	$\frac{\rho \text{ GREEN} - \rho \text{ RED}}{\rho \text{ RED} + \rho \text{ GREEN}}$	(Tucker, 1979)
TCARI	Transformed Chlorophyll Absorption in Reflectance Index	$3 * \left[\frac{(\rho \text{ RED EDGE} - \rho \text{ RED}) - 0.2}{(\rho \text{ RED EDGE} - \rho \text{ GREEN})} \right] * (\rho \text{ RED EDGE} / \rho \text{ RED})$	(Haboudane et al., 2002)

Determination of NNI

To reliably determine NNI, the method introduced by Bohman et al. (2023) based on a partially-pooled Bayesian hierarchical framework was selected. This approach, based on Bayesian hierarchical framework developed by Makowski et al. (2020), allowed for robust estimation of the parameters of the CNDC, accounting for variations between locations and varieties. The dataset employed in Bohman et al. (2023) was expanded through the integration of Ciampitti's global dataset Ciampitti et al. (2022) and additional experimental data obtained in the present study. The combined dataset presents substantial variability in genetics, climatic conditions and agricultural management practices.

Detailed descriptions of the original datasets are provided by Bohman et al. (2023) and Ciampitti et al. (2022). To further enhance this integrated dataset, we included data specific to the potato cultivar 'Oleva', cultivated in Denmark. This data comprises mid-season plant biomass and %N measurements from N response plots for the years 2018 and 2019 (Tab. 1b), alongside data from fully irrigated field plots collected in 2017 (Tab. 1a).

Overall, the comprehensive dataset study provides data on potato experiments involving 16 distinct cultivars grown across six countries, resulting in 18 unique variety-location combinations. A graphical overview of the dataset is presented in Fig. 2, with detailed information provided in Tab. 4.

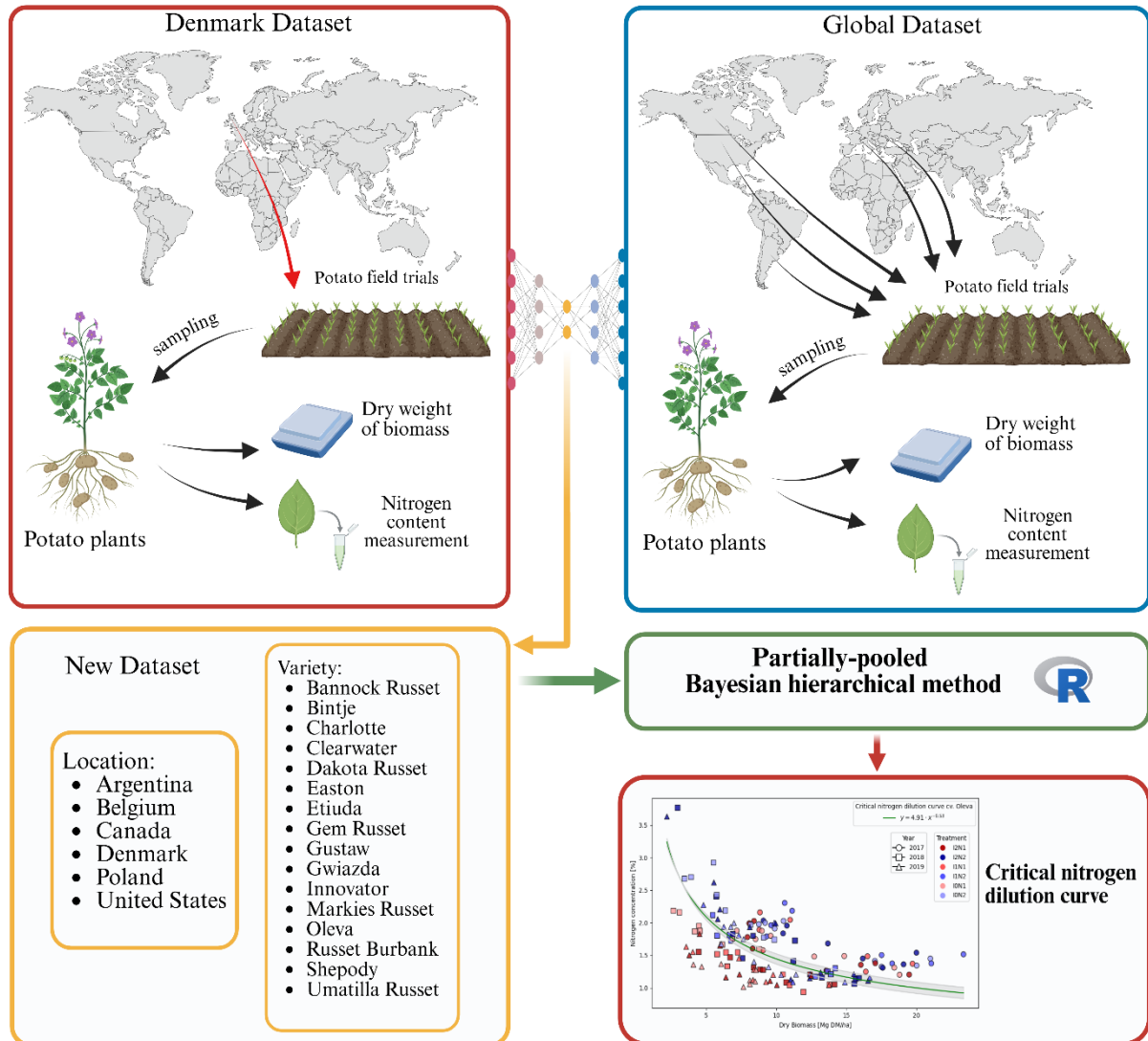


Fig. 2. Graphical representation of the nesting process for integrating data from this study, the Denmark dataset (left), with data from Bohman's and Ciampitti's study (Bohman et al., 2023; Ciampitti et al., 2022), the Global dataset (right). New dataset comprising 16 cultivars from 6 different location was used to fit the partially-pooled Bayesian hierarchical method and to obtain α and β parameters across different cultivars and countries (summary in Tab. 4).

Tab. 4 Summary of the experimental dataset object of this study used to fit the partially-pooled Bayesian hierarchical model.

Country	Cultivar	N° of samples	Reference
Argentina	Bannock Russet	52	(Giletto et al., 2020)
	Gem Russet	72	
	Innovator	72	
	Markies Russet	36	
	Umatilla Russet	56	
Belgium	Bintje	234	(Abdallah et al., 2016)
	Charlotte	114	
Canada	Russet Burbank	104	(Giletto et al., 2020)
	Shepody	104	
Denmark	Oleva	28	Present Study
Poland	Etiuda	14	(Trawczynski, 2019)
	Gustaw	15	
	Gwiazda	15	
United States (US)	Clearwater	30	(Bohman et al., 2023)
	Dakota Russet	70	
	Easton	70	
	Russet Burbank	328	
	Umatilla Russet	30	

The method described by Makowski et al. (2020) and subsequently implemented by Bohman was based on modelling the relationship between %N and DM, accounting for variations between locations and varieties and incorporating uncertainty in the parameter estimates of the model. The method relied on two main components. The first was a linear-plateau curve that describes the relationship between %N and DM, with DM increasing up to a maximum value (plateau) at a N_c .

$$DM = \min (DM_{max,i} + S_i * (\%N_{plant} - \%N_c), DM_{max,i}) \quad (1)$$

Where min is the minima function (i.e. the plateau component), $DM_{max,i}$ the maximum dry biomass value for a specific date i , S_i represents the slope of the linear-plateau curve, $\%N_{plant}$ the N concentration of the plant and $\%N_c$ the critical N concentration.

The second component is a negative exponential curve that describes the relationship between $DM_{max,i}$ and $\%N_c$.

$$\%N_c = \alpha DM_{max,i}^{-\beta} \quad (2)$$

Where α and β are the parameters that define the CNDC.

Combining the equations (1) and (2), a unified non-linear model formula was used in *brms* package as follow:

$$DM = \min (DM_{max,i} + S_i * (\%N_{plant} - (\alpha DM_{max,i}^{-\beta})), DM_{max,i}) \quad (3)$$

To handle experimental variability in the hierarchical Bayesian model, the parameters S and DM_{max} were modelled with group-level effects for each sampling date, i , while the parameters α and β were modelled with effects for location and cultivar within the location. In this way, the model accounted for the complex interactions between genotype, environment and management. The model was fitted using the *brms* package in R environment (Bürkner, 2017; R Core Team, 2024), which was an interface for Stan capable of handling complex models with random effects. To incorporate prior knowledge into the model, informative priors were defined following the framework detailed by Bohman et al. (2023). Briefly, this process involved integrating expert knowledge, previously reported parameter estimates, empirical insights from the dataset summary statistics, and evaluation of joint prior predictive distributions. Priors were adjusted whenever initial specifications led to biologically implausible outcomes or convergence difficulties. Physiological constraints were explicitly enforced by restricting parameters such as S and DM_{max} to strictly positive values (lower bounds > 0), ensuring consistency with the biological relationship between W and $\%N_{plant}$. A Student's t distribution was used as the prior for the parameter σ , whereas Normal prior distributions were assigned to all other parameters. Model fitting was performed with four Markov chains, each of 10,000 iterations, including 3,000 iterations as warm-up. Convergence diagnostics confirmed satisfactory performance, with all parameters achieving R-hat values below 1.01 and effective sample sizes (bulk-ESS and tail-ESS) exceeding 100 samples per chain. The goal was to leverage the advantages of partial pooling to make direct inferences on the levels of $G \times E \times M$ interaction, even when experimental data were limited. One of the main innovations of the adopted method was that it does not require a preliminary classification of N-limited or non-

limited conditions to identify $\%N_c$ values, as was the case in previous methods. Additionally, it facilitates the analysis of uncertainty in the model parameters and the estimated CNDC.

For each sampling date, the NNI was calculated as the ratio between the $\%N_{Plant}$ and $\%N_c$ estimated from the CNDC (3).

$$NNI = \frac{\%N_{Plant}}{\%N_c} (3).$$

ML models for NNI predictions using UAV multispectral based imagery

The NNI values derived from the partially-pooled Bayesian hierarchical model, associated with each plot for each date, were used as targets for training the ML models. Multispectral images acquired by UAV on the same dates when plant sampling for NNI determination was performed were used as predictors. The complete dataset, comprising the NNI values along with the spectral band data and VIs derived from the UAV multispectral images, was used for the analysis. In total, the dataset included 22 input variables, with NNI as the target, and was imported into MATLAB (R2024b). To identify conditional dependencies between variables and enhance predictions, this study employed the ReliefF algorithm for feature selection. This algorithm efficiently removes irrelevant features and improves the computational efficacy of predictions (Robnik-Šikonja and Kononenko, 2003; Zhang et al., 2025). A total of 12 variables were selected. The dataset was randomly divided into a validation set, representing 70% of the total dataset, and a test set, representing 30% of the total one. In addition, a randomized 5-fold cross-validation was performed to mitigate overfitting risk and ensure robust estimation of model performance. Using MATLAB and the Regression Learner toolbox, several models were trained and tested, including linear regression, support vector machines, gaussian process regression (GPR), stepwise linear regression, ensemble of trees and neural networks (For a full description of the hyperparameter settings, see Tab. S1, in supplementary materials). Model outputs were processed using metrica webtool (Correndo et al., 2022). The metrics used to evaluate the results were chosen from a wide range of performance scores available on webapp based on R package developed by Adrian et al. (2023). This tool provides a user-friendly framework for assessing predictive performance of models, including error metrics, error decomposition, efficiency, indices of agreement, goodness of fit, adjusted and symmetric correlation coefficient. For model comparison, four key metrics were selected: Coefficient of

determination (4), root mean square error (5), mean squared error (6), and mean absolute error (7), calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

Where y_i is the observed value, $\hat{y}_i$ is the predicted value and $\bar{y}$ is the mean of the observed value. A total of 45 performance metrics were computed; the complete results are presented in Tab. S2 (see supplementary materials).

NNI maps creation

The NNI map prediction was conducted within Python environment (Python Software Foundation, 2023) utilizing *matlab.engine* (for Python-MATLAB integration), *os* (for handling file and directory operations), *rasterio* (to read and write raster data) and *numpy* (for array manipulation and mathematical computations) libraries. The workflow began with the import of TIFF-format images, which were subsequently transformed into matrices and then arrays. These arrays were converted into MATLAB tables to enable prediction modelling using MATLAB's analytical framework. Once the predictions were complete, the resulting data tables were converted back to TIFF format. This prediction process was iteratively applied to the datasets from each UAV flight, resulting in a total of 28 NNI maps, specifically 3 maps for 2017, 16 for 2018, and 9 for 2019. The resulting NNI maps exhibited a high spatial resolution (~0.04–0.09 m/pixel), consistent with the native resolution of the original image files (See details in Tab. 2). Following the forecast, these maps were subjected to geostatistical analysis to assess spatiotemporal trends. Focusing on areas subjected to specific treatments, pixel data were extracted from the NNI estimates and analysed with geostatistical algorithms to investigate the spatial distribution and temporal evolution of crop N status.

Statistical Analysis

To assess the effects of N fertilization and irrigation on the NNI, a comprehensive statistical analysis was conducted. For each map, the predicted NNI characteristics, including mean, median, minimum, maximum, and standard deviation, were extracted for each plot using the *Zonal Statistics* plugin in QGIS. The mean value was selected as the representative parameter for each plot. The extracted data were then processed in R software, where a two-way analysis of variance (ANOVA) was performed, followed by Tukey's multiple comparison test. The analysis used NNI as the dependent variable, with N and irrigation levels as factors. A significance level of 99% ($p < 0.01$) was applied.

Results

Building CNDC using partially-pooled Bayesian hierarchical method

Fig. 3 shows the variability of the coefficients α and β as calculated by the partially-pooled Bayesian hierarchical model. The boxplots illustrate the distribution of values for each variety, categorized by country of origin (Argentina, Belgium, Canada, Denmark, Poland and US), with medians highlighted by a red line and labelled with numbers above each box. Overall, α values exhibited limited variation among varieties and countries. Cultivars from Argentina, such as Bannock Russet, Gem Russet, Innovator, Markies Russet and Umatilla Russet, had median values ranging from 4.93 to 4.95 (Fig. 3a). For Belgian cultivars, Bintje showed a median value of 4.72 and Charlotte 4.74. A higher α was calculated for the Danish cultivar Oleva 4.91 (Fig. 3a), similar to the Polish cultivars, whose medians ranged from 4.91 to 4.92. On the other hand, the β values showed a more pronounced variability among both countries and cultivars. For example, the Argentinian varieties had relatively low β values, clearly different from those of the other countries, with medians ranging from 0.14 to 0.21. On the other hand, the Belgian varieties (Bintje and Charlotte) had higher β values, with medians of 0.59 and 0.57, respectively (Fig. 3b). However, a common pattern in US was that both α and β coefficients showed little variability for all varieties (Fig. 3).

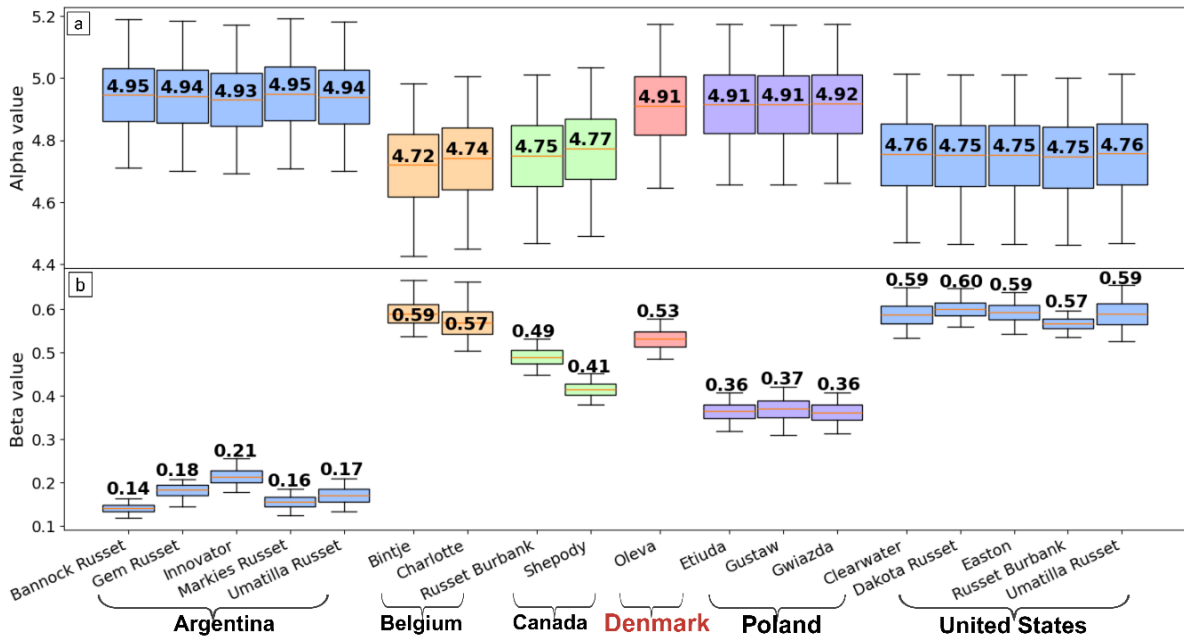


Fig. 3. Distribution of α (a) and β (b) values in Argentina, Belgium, Canada, Denmark, Poland and US for different cultivars (summary on Tab. 4). The end of the vertical line for each boxplot represents, from top to the bottom, the 10th percentile and the 90th percentile. The horizontal line of the box's limit, from the top to the bottom represents the 25th, median, and 75th percentile, respectively. The red line represents the median value with numerical value shown.

The parameters α and β from the Danish cultivar ‘Oleva’ were used to model the CNDC. Fig. 4 shows the relationship between crop %N and DM for this cultivar. The CNDC, shown in green, represents the model’s central estimate, described by the function $y = 4.91 x^{-0.53}$ (Fig. 4). Points, squares and triangles indicate observations from the growing seasons 2017, 2018, and 2019 respectively, highlighting the variability of %N relative to DM. A general trend of decreasing %N with increasing DM was observed, reflecting a typical N dilution effect in growing crops. Some degrees of dispersion are observed, particularly evident at intermediate biomass levels, where the observations tend to deviate more from the central curve. At higher biomass values, a greater distance between the observed values and the curve is noted, suggesting higher %N levels compared to the critical values.

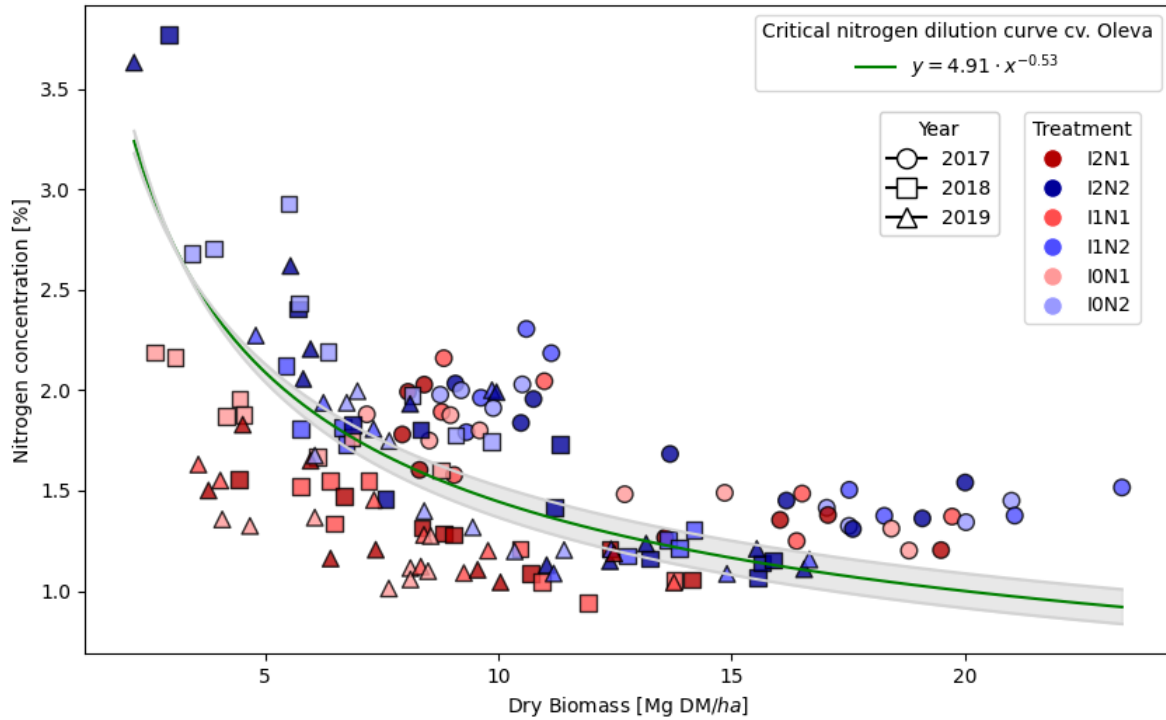


Fig. 4. Relationship between %N (%) and DM (Mg DM/ha) for the potato cultivar 'Oleva' cultivated in Denmark. Points, square and triangles represent observed data respectively for 2017, 2018, 2019, while the green curve and shaded confidence interval are the outputs of a Bayesian model. Different shades of blue for N2 and red for N1 represent the different treatments. Interquartile range between the 5th and 95th percentile defined the confidence interval, depicted in grey. Points above the line represent luxury N content.

Performance of ML models for NNI predictions using UAV Multispectral based imagery

The overall performance of the six different ML models in predicting NNI was satisfactory and comparable across both the validation (V) and test (T) datasets, as shown in Fig. 5. The GPR model performed best among the models evaluated, with R^2 of 0.83 on both the V and T dataset, indicating a strong ability to explain the variability within the dataset. This model had the lowest RMSE and MSE values, with an RMSE of 0.11 for the V dataset and 0.10 for the T dataset and an MSE of 0.01 for both V and T. This model also obtained the highest prediction speed of 46810.25 observations per second (obs/s). The Shapley importance graph that explains the contribution of each feature for GPR model is reported in Fig. S1 (see supplementary materials). The Stepwise Linear Regression model had an R^2 of 0.81 the V data and 0.82 for T data, comparable to the GPR, with a RMSE equal to 0.11 and a prediction speed equal to 10364.86 obs/s, 77% lower than the GPR. The Support Vector Machine model gave a satisfactory result

for both V and T (0.80), with a prediction speed of 22499.02 obs/s. Although it did not match the performance of the best models, its results were still acceptable, albeit with higher RMSE and MSE values, indicating lower predictive accuracy. The Ensemble tree showed slightly lower R^2 values, particularly on the T data (0.79). Comparable results were obtained for Neural Network, that achieved R^2 values of 0.76 for V data and 0.79 for T data, with a RMSE of 0.12 for V data. On the other hand, the Linear Regression model had the weakest performance, with an R^2 of 0.72 on the V and 0.67 on the T. It had the highest values of RMSE (0.14) and MSE (0.02), which were 28% and 65% higher, respectively, compared to those obtained with GPR, which could indicate the inability of this model to capture that much of the variability and providing reliable predictions (Fig. 5).

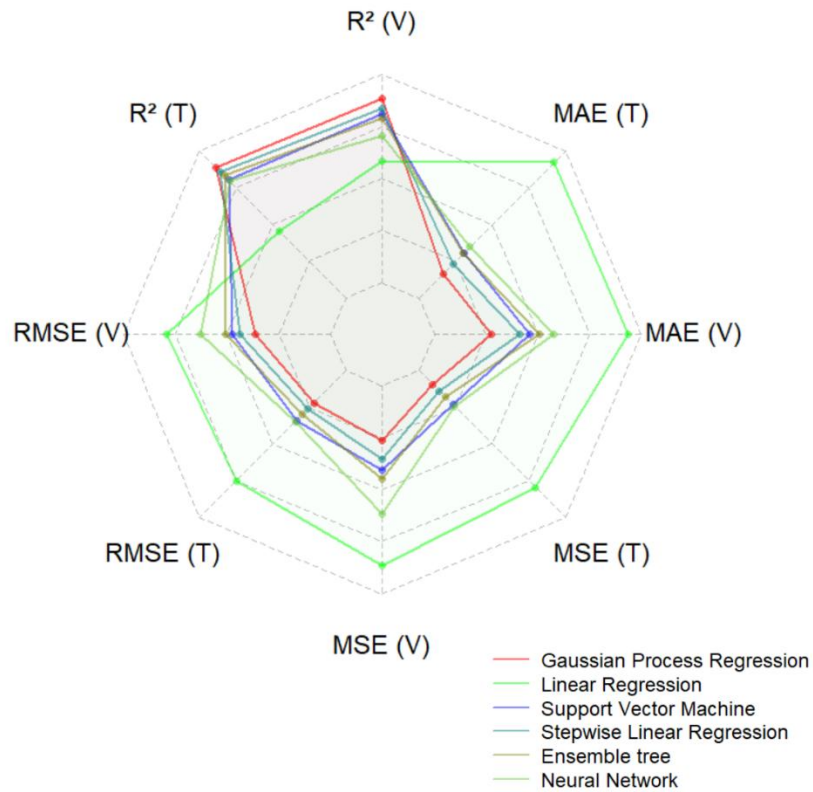


Fig. 5. Graphical representation of performance metrics for six ML models (GPR, support vector machine, linear regression, stepwise linear regression, ensemble tree and neural network) on V and T datasets. The radar plot compares six models across multiple metrics, with each axis representing a specific evaluation criterion (R^2 , RMSE, MSE, MAE).

Spatial and temporal evaluation of UAV multispectral-based NNI

Fig. 6 shows the spatial pattern of predicted NNI as captured from the drone image (Fig. 6a), colour coded for each treatment (Fig. 6b), and the mean between three years and three replicates of each treatment of the temporal trend of NNI values expressed in DAE (Fig. 6c). The predicted NNI values clearly show how different plots (with water and N interactions) had different evolution during the growing season. For example, I1N1 had average values of 0.98 while I1N2 had 1.04. For the rainfed plots (I0), N1 and N2 showed a range of values of 0.97 and 1.04 respectively. Fig. 6b shows a colour coded grid representing the different treatment combinations, with each colour corresponding to a particular line in Fig. 6c. Fig. 6c shows the overall trend of NNI values, which ranged from 0.80 to 1.20, with a clear separation between the N1 and N2 plots. The temporal difference between all treatments was minimal during the first 15 DAE, then it became more pronounced during the late growing season, peaking at about 45 DAE for N2 and 38 DAE for N1 (Fig. 6c). For the N2 treatments, NNI values remained initially stable, then significantly increased throughout the growing season and finally declined as plants entered senescence. In contrast, the N1 treatments showed a more gradual increase in NNI followed by an earlier decline around 38 DAE. Within each N treatment, irrigation levels influenced the temporal response of NNI. I0 treatment for N2 peaked at around 45 DAE with a higher value of 1.15 and was then lower than I1 and I2 between 48 and 60 DAE. I0 treatment for N1 also showed lower NNI values between 15 and 35 DAE but later showed a contrasting pattern with higher NNIs relative to I1 and I2 between 65 and 90 DAE (Fig. 6c).

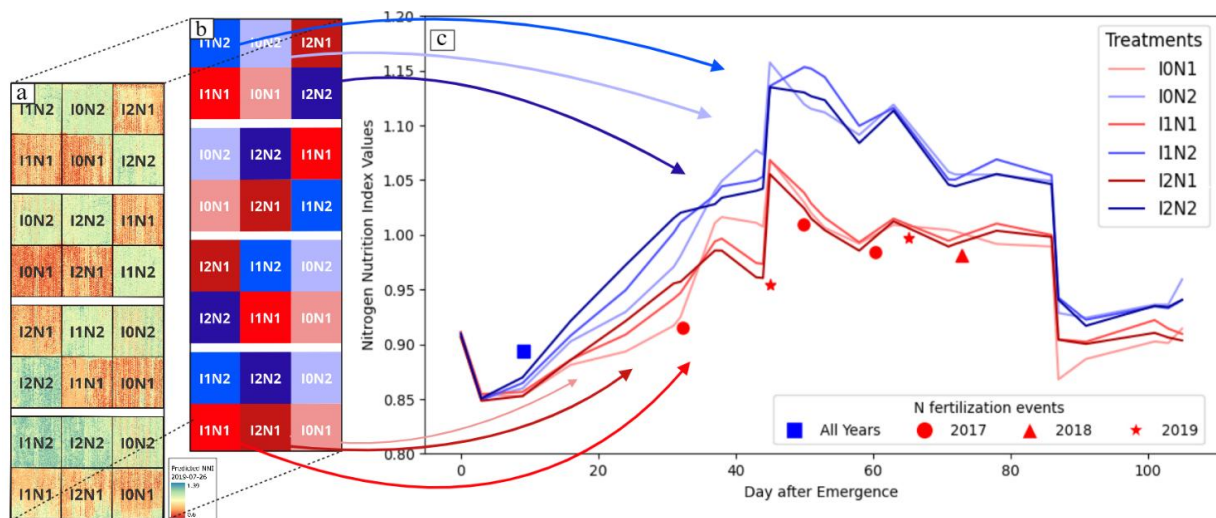


Fig. 6. NNI predicted map for (a) irrigation and N treatments (53 DAE) with green colour representing higher NNI values and red colour lower values; (b) the different treatments were colour-coded with different shades of blue for N2 and red for N1. Data were then plotted (6c) as function of

DAE with each line representing a specific treatment. Markers indicate N fertilization dates: circles for 2017, triangles for 2018, stars for 2019 and squares for N2 post emergence fertilization in all three years.

The variation of NNI index for the six treatments in the different growing seasons is represented in Fig. 7. Overall, NNI values ranged between 0.75 and 1.40 among treatments and growing seasons (Fig. 7a). In 2017, NNI values were notably higher respect to other growing seasons (Fig. 7b). N2 treatments had statistically significant higher values than N1 at all the different irrigation levels and for all the growing seasons ($p < 0.01$) (Fig. 7a-d). However, irrigation as an independent factor and its interaction with N levels had not a statistically significant impact on mean NNI values.

The growing season 2017 was characterized by higher N supply and substantial rainfall in the early part of the season (53 mm in May, 90 mm in June and 90 mm in July); the NNI values had a median of approximately 1.32 for N2 treatment and 1.18 for N1 treatment (Fig. 7a). The yield for 2017 reached 60 Mg ha⁻¹ of fresh tuber mean weight (63 ± 7.4 for N2, 57 ± 7.5 for N1). In contrast, 2018 was a year with lower and later N supply and rainfall (21 mm in May, 26 mm in June and 5 mm in July), so it displayed lower NNI values, ranging between 0.78 and 1.15, and the mean yield was 40 Mg ha⁻¹ of fresh tuber weight (45 ± 11.6 for N2 and 37 ± 10.7 for N1) (Fig. 7c). Similarly, in 2019, NNI values ranged between 0.75 and 1.12 (Fig. 7d). Rainfall during this season was slightly higher, with 58 mm in May, 47 mm in June and 63 mm in July and the mean yield was 38 Mg ha⁻¹ of fresh tuber weight (43 ± 8.3 for N2 and 34 ± 6.4 for N1).

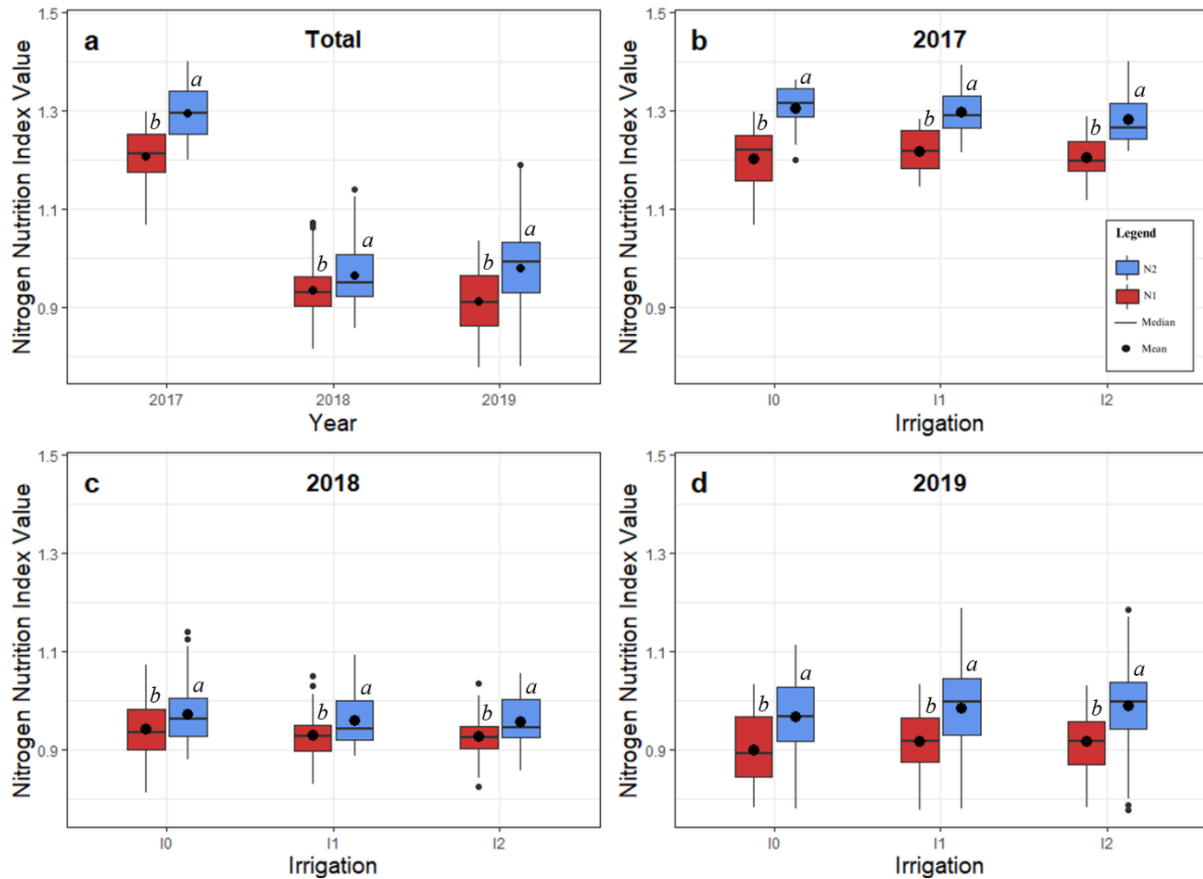


Fig. 7. Boxplots of the predicted NNI values at different irrigation (I_0 = minimum, I_1 =optimized, I_2 = full) and N treatments (with N_1 = optimized, red boxplots; N_2 = full, blue boxplots) as plotted (a) for all the growing seasons; (b) for the growing season 2017; (c) 2018; and (d) 2019. Letters "a" and "b" indicated statistically significant differences between treatments for each growing season. For each boxplot, the end of the vertical line represents, from top to the bottom, the 10th percentile and the 90th percentile. The horizontal line of the box's limit, from the top to the bottom represents the 25th, median, and 75th percentile, respectively. The Box limits indicate the range of central 50% of the data with a black line marking represents the median and the dot the mean.

Discussions

In this study, the combination of partially pooled Bayesian hierarchical method and RS imagery data allowed the spatial estimation (within-field) of NNI on potato crop.

The partially pooled Bayesian hierarchical approach provided robust results, identifying α and β parameters and quantifying the variability in the estimation of α and β parameters among cultivars and regions. The variability of these parameters across cultivars and regions reflects distinct crop-environment interactions adapted to local conditions, while maintaining a consistent physiological pattern. In particular, the parameter α exhibited moderate variation

across and within regions and cultivars, whereas β showed greater variability, probably influenced by photoperiod and planting density. This variability is not exclusive to potato crop, as similar patterns have been observed in other crops, such as maize (Ciampitti et al., 2021a) and rice (Lacasa et al., 2023). Bohman et al. (2023) discussed the underlying causes of this variability in potatoes, highlighting how the genotype, management and environment interactions play an important role in the variation of CNDC parameters. The authors also noted that factors related to ‘non-ideal’ experimental setups and datasets (such as a bias toward N-limiting conditions in Argentina and toward non-N-limiting conditions in Belgium and the USA) may introduce distortions in the estimation of the CNDC.

In this study, for the Oleva cultivar grown in Denmark the obtained parameters were 4.91 for α and 0.53 for β . The ground sampled data were mostly above the curve for the 2017 growing season, while a clear separation between N1 and N2 treatment was observed for 2018 and 2019. This could be due to the early and more abundant rainfall and higher fertilisation in the 2017 growing season. The results reported here are comparable with those of Peng et al. (2021), who applied the Duchenne curve (Duchenne et al., 1997), developed by cultivars Bintje and Kaptah, to the same dataset. That curve had slightly different values from those obtained in the present study, especially for low biomass values, where the latter better discriminates graphically among different N treatments (Fig. S2 in supplementary materials). This further supports previous studies indicating that CNDCs can vary due not only to differences in genotype, environment, and management but also significantly as a function of the statistical method employed. Lacasa et al. (2023) analysed this issue comparing hierarchical Bayesian framework and conventional sequential frameworks; results reported that the Bayesian approach outperformed the conventional framework under most of the conditions, particularly for datasets characterized by limited or biased samples. Under such conditions, the sequential framework produced unreliable estimates, primarily due to small-sample bias in maximum likelihood estimators and neglecting uncertainty in the estimation of $\%N_c$ and DM_{max} . Conversely, the hierarchical Bayesian model integrates all available data simultaneously, accounting the uncertainty estimation and incorporating prior knowledge to refine inference accuracy. Uncertainty analysis remains a critical and highly relevant aspect when evaluating CNDCs. A recent reanalysis of published data on tall fescue, wheat, and maize, originally collected to assess variations in CNDC parameters under water-limiting conditions using a sequential framework, investigated the assumption that N dilution mechanism significantly changes with water availability (Ciampitti et al., 2021b). The study, which also explored the

physiological basis of N dilution in plant tissues, indicated that when uncertainty is properly accounted, there is no conclusive evidence of a water availability effect on CNDC parameters. As a result, the authors suggest the use of a more universal CNDCs to estimate NNI under varying water conditions (Ciampitti et al., 2021b). However, Fernandez et al. (2022) emphasize that despite the hierarchical Bayesian method's inherent suitability for smaller datasets, the quality and quantity of experimental data remain critical factors influencing model reliability. Their findings showed a clear reduction in bias and model error with increasing data quality and quantity. Consequently, they propose detailed guidelines on selecting priors, specifying an ideal number of experimental trials, N fertilization levels, sampling events, biomass and N ranges, and data variance to mitigate inferential biases. In this contest the partially pooled approach to hierarchical Bayesian framework emerges as a balanced solution between fully pooled and non-pooled models. As seen in this study, the partial pooling facilitates specific inferences at each hierarchical level (e.g. cultivar or site), while simultaneously integrates multiple datasets, thus reducing data requirements per group. Nevertheless, as seen in Bohman's work (Bohman et al., 2023) even partially pooled Bayesian model can experience negative impacts when dealing with imbalanced datasets, though these effects are substantially lower compared to traditional frequentist methods. In the experimental trials conducted in this study, the authors observed a degree sensitivity of the Bayesian model's outputs to variations in the characteristics in the training dataset. Specifically, when the model was trained exclusively on data from the main field, it yielded significantly different CNDCs (data not shown). This confirm that training the model on a biased dataset, containing limited representation of N regimes and the presence of environmental stressors, can significantly influence the estimation of CNDC parameters. This finding underscores the necessity for further investigation to systematically evaluate and quantify the sensitivity of CNDCs generated with partially pooled hierarchical models to the variations in composition and size of site-specific datasets.

Comparison of ML models for NNI prediction using UAV multispectral data

The ML models applied to UAV multispectral data accurately identified crop N status through NNI estimation. Consistent with finding from other studies in this topic, ML models demonstrated strong ability to learn complex and nonlinear relationships between multispectral signals and crop nutritional status. This characteristic makes them highly effective in estimating parameter related to N, like NNI, even when faced with variation in field conditions (Jiang et

al., 2023; Li et al., 2024). In addition to their predictive capabilities, ML algorithms provide a valuable level of interpretability by enabling transparent examination of the relationships between input variables, thereby facilitating the identification of relevant parameters. This feature becomes particularly important in scenarios involving small to moderately sized datasets; where more complex approaches such as deep learning often suffer from overfitting and reduced generalizability (Ennaji et al., 2023). The combination of spectral bands and VIs as inputs further enhanced predictive power. This result agrees with the findings of Zhang et al. (2024) and Peng et al. (2021), as well as studies where UAV were applied for estimating N crop status (Pereira et al., 2022) and other agronomic parameters (Lussem et al., 2022; Shafiee et al., 2021). Compared to the other ML algorithms, GPR method more accurately estimated potato NNI. Zhang et al. (2024) also documented that the GPR model demonstrated satisfactory performance in the estimation of the NNI on wheat; while Xu et al. (2023) reported good results with the same model for estimating leaf N content in rice. The GPR is not only capable of modeling nonlinear relationship between variables but also demonstrated strong suitability for small sample datasets (Liu et al., 2023). Such features are particularly robust and valuable for informed decision-making and efficient resource management in agricultural applications.

Spatiotemporal variability assessment of predicted NNI

Precision N management has been extensively investigated, with numerous studies emphasizing the critical importance of spatial variability of crop N status, particularly in cereals and potatoes (Goffart et al., 2023; Li et al., 2022; Wang et al., 2022). Nonetheless, despite substantial research effort, the study of the temporal and spatial evolution of the NNI remains a relatively poorly explored topic. Most of the existing research has primarily concentrated on refining non-destructive monitoring techniques, either by directly applying sensor-based systems or integrating their estimations into crop models to improve their predictive capabilities (Gislum et al., 2021; Silva et al., 2023).

In this study the analysis of NNI maps enabled both graphical and quantitative discrimination of the effects of different fertilization and irrigation regimes over time (Fig.6; Fig.7; Fig.S3 in supplementary materials). These findings align with the study conducted by Peng et al. (2021) who demonstrated the capability of mid-season data to differentiate crop N conditions based on NNI. However, that study did not consider the temporal evolution of NNI, which, as evidenced in our results, is highly informative. The observed spatiotemporal trends in NNI values give

strategic information about the interactions between agronomic management practices and environmental conditions. The spatial variability in NNI is driven by multiple interacting factors, including soil heterogeneity, fertilization strategies, and canopy characteristics (Fig. S3). Soil properties, particularly variations in texture, organic matter content and nutrient retention, significantly affect nitrogen availability and subsequent uptake by the crop, resulting in distinct spatial patterns of NNI across fields (Fig. S3) (Canicattì et al., 2025a; Maestrini and Basso, 2018; Schuster et al., 2023). The observed variability is further reinforced by canopy development patterns, as healthier plants with adequate N availability typically exhibit denser canopies and higher reflectance in the near-infrared spectral region (Schuster et al., 2023; Su et al., 2024). Consequently, RS-based NNI maps effectively captured these agronomic-driven differences in crop N status. The results from this study also highlight a dynamic evolution of NNI throughout the growing seasons and between different seasons, influenced by fertilization, irrigation and climatic differences.

In the early stages of the growing season, prior to fertilization, no significant treatment differences were observed; subsequently, NNI reached a mid-season peak, coinciding with the early flowering stage. This stage was also characterized by the biggest gap in NNI between N1 and N2. A similar mid-season NNI peak was reported by Pei et al. (2023) in a study conducted in cotton, where NNI values reached the highest level of the season approximately 110 days after sowing. This stage marked the transition from vegetative to reproductive growth, before the start of decline in the remainder of the season. Similar pattern was also reported by Z. Chen et al. (2019) in winter wheat, with a peak at 65 days after planting. If consistently confirmed across crops and environments, this dynamic could provide an interesting and useful framework for identifying phenological stages based on NNI dynamics.

These observations underscore the potential of NNI dynamics as a tool to investigate time-dependent effects of fertilization strategies and environmental factors, such as N leaching and emissions. For instance, the differences in N treatments identified in this study aligned with process-based model estimates of leaching, indicating higher N losses under the N2 regime (51 kg ha⁻¹) compared to N1, which exhibited lower leaching levels (43 kg ha⁻¹) (Lord and Shepherd, 1993; Manevski et al., 2018). Application of this approach on a broader scale, could improve our understanding of critical environmental dynamics.

Furthermore, the NNI mid-season peak consistently aligned with the most strongly correlated period with yield, reinforcing the importance of precise temporal monitoring. Across all the

three years of the study, this peak coincided with the most yield-informative stage, underscoring the potential of NNI as a real-time indicator of crop productivity. The observed correlation between NNI and yield was moderate to strong ($R^2 = 0.46\text{--}0.68$; Table S3 in supplementary materials). These findings are consistent with those on (Rodriguez et al., 2024), who emphasized the universality of the yield-NNI relationship across the major crop species.

Notably, the variation of this correlation throughout the season highlights the importance of timing. Specifically, correlation of NNI with yield grew to a maximum value occurred at DAE 45, suggesting that the temporal aspect of NNI measurements could significantly influence the application on precision management. Overall, the temporal and spatial assessment of NNI offers important insights into N dynamics and crop performance.

Limitations, challenges and future research directions

The use of a Bayesian hierarchical approach combined with RS multispectral data enabled the within-field spatial estimation of NNI in potato crops, providing valuable insights into NNI dynamics and its functional relationship with key agronomic and environmental parameters, such as yield and nitrogen leaching. Specifically, this approach integrated partially pooled hierarchical Bayesian modeling of site-specific CNDC parameters with UAV data to spatialize NNI predictions across space and time. Combining these methodologies facilitates the scalability of UAV-based N management and promotes broader, practical application of CNDCs. The ability of Bayesian models to integrate new site and cultivar-specific datasets into global data pools via partially pooled hierarchical structures reduces the need for extensive, long-term experiments while maintaining high prediction accuracy. Consequently, ML models can be effectively trained with NNI data derived from site-specific CNDCs, minimizing initial bias and enhancing their specific practical applicability for N management within existing precision agriculture systems.

While this framework opens promising avenues for future research and large-scale deployment, certain limitations still persist and are accordingly considered.

In the development of the CNDC, incorporating additional potato cultivars across different countries, genetic background and a range of growing conditions and management practices (e.g. rainfall vs irrigated system or conventional vs organic farming) would enhance the robustness and generalizability of the findings. Expanding the dataset with a wider

representation of climatic zones, soil types, and fertilization regimes would further improve the accuracy of the outputs and reduce the uncertainty in predictions.

For the ML-based NNI prediction model, testing the impact of different UAVs flight timings or integrating proximal sensing technologies with remote sensing could improve the accuracy of NNI assessments, providing more spatial and temporal resolution and insights.

Evaluating NNI dynamics across a wider range of field conditions and N levels, including reduced fertilizer scenarios, may contribute to better understand the trade-offs between N supply and crop productivity.

To improve the scalability of this framework beyond potato, future research should explore its applicability to other crops with different N use efficiencies and canopy structures, such as cereals, legumes or horticultural crops. This could be achieved by training ML models on multispecies datasets that incorporate spectral and physiological traits of the different crops. In addition, incorporating crop-specific CNDCs into the ML framework could improve predictive performance in different agroecosystems.

From a technological perspective, the incorporation of new deep learning architectures could be explored to enhance model robustness, particularly when managing larger and more complex datasets. Additionally, a comparative evaluation between different RS platforms would help clarify their respective strengths and limitations of each platform, potentially supporting a multi-scale monitoring strategies through data fusion techniques.

A deeper investigation on the interactions between NNI and yield, as well as the links between seasonal NNI dynamics and N leaching (and other N losses), in relation to timing effects would help to clarify the broader environmental implications of N management strategies.

Finally, validation of this framework across different agro-ecological zones and climate conditions will be crucial to ensure its generalizability and practical applicability.

Overcoming the limitations of these will open wider prospective in enabling future research to further optimize the N precision management and reduce environmental impacts as based on the findings herein presented.

Conclusions

Overall, the integration of UAV-acquired multispectral data with the GPR model allowed for effective estimation of NNI and identification of N status variations in crops throughout the growing seasons. The partially pooled Bayesian hierarchical method enabled the acquisition of reliable ground-truth-based NNI estimates, demonstrating the robustness of the approach. This approach successfully detected luxury and stress in N status and identified significant differences among various N management regimes, underscoring a powerful framework for assessing crop N dynamics.

The temporal analysis of predicted NNI confirms the model's ability to detect and differentiate crop N status over time. To enhance the generalizability and scalability of this approach, future studies should explore its application across diverse crop types and agro-environmental conditions. This includes analysis of NNI dynamics under diverse N inputs and field conditions, as well as to extend the framework to crops characterized by varying canopy structures and NUE. This could be achieved by incorporating multispecies datasets and crop-specific CNDCs into the modeling process. Addressing practical challenges, such as operational scalability, processing time and cost-effectiveness will be key to facilitate broader applications, supporting precision N management strategies and sustainable agricultural practices.

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Supplementary materials

Tab.S1 Summary of hyperparameters used to train the compared models object of the study.

Model hyperparameters	Gaussian process regression	Support vector machine	Stepwise linear regression	Neural network	Ensemble trees	Linear regression
Preset	<i>Exponential GPR</i>	<i>Quadratic SVM</i>	<i>Stepwise linear</i>	<i>Medium Neural Network</i>	<i>Bagged Trees</i>	<i>Linear</i>
Basis function	<i>Constant</i>					
Kernel function	<i>Exponential</i>	<i>Quadratic</i>				
Kernel scale	<i>Automatic</i>	<i>Automatic</i>				
Isotropic Kernel	<i>Yes</i>					
Box constraint		<i>Automatic</i>				
Epsilon		<i>Automatic</i>				
Inizial terms			<i>Linear</i>			
Number of fully connected layer				<i>1</i>		
First layer size				<i>25</i>		
Activation				<i>ReLU</i>		
Iteration limit				<i>1000</i>		
Minumum leaf size					<i>8</i>	
Number of learners					<i>30</i>	
Maximum number of steps			<i>100</i>			
Standardize data		<i>Yes</i>		<i>Yes</i>		
Signal standard deviation	<i>Automatic</i>					
Optimization numeric parameters	<i>Yes</i>					
Feature selection	<i>12/22 using RReliefF</i>	<i>12/22 using RReliefF</i>	<i>12/22 using RReliefF</i>	<i>12/22 using RReliefF</i>	<i>12/22 using RReliefF</i>	<i>12/22 using RReliefF</i>
PCA	<i>Disabled</i>	<i>Disabled</i>	<i>Disabled</i>	<i>Disabled</i>	<i>Disabled</i>	<i>Disabled</i>
Optimizer	<i>N/A</i>	<i>N/A</i>	<i>N/A</i>	<i>N/A</i>	<i>N/A</i>	<i>N/A</i>

Tab. S2 Metrics summary of predictive performance of GPR, including error metrics, error decomposition, efficiency, indices of agreement, goodness of fit, adjusted and symmetric correlation coefficient.

	Metric	Metric Long Name	Validation Score	Test Score
1	B0	Intercept of SMA regression	0.102	0.073
2	B1	Slope of SMA regression	0.903	0.937
3	r	Pearson's correlation coefficient	0.91	0.911
4	R2	Coefficient of determination	0.827	0.829
5	Xa	Accuracy coefficient	0.995	0.997
6	CCC	Concordance correlation coefficient	0.905	0.908
7	MAE	Mean Absolute Error	0.081	0.076
8	RMAE	Relative Mean Absolute Error	0.078	0.074
9	MAPE	Mean Absolute Percentage Error	8.453	7.672
10	SMAPE	Symmetric Mean Absolute Percentage Error	8.249	7.551
11	RAE	Relative Absolute Error	0.377	0.398
12	RSE	Relative Squared Error	0.173	0.173
13	MBE	Mean Bias Error	-0.002	-0.008
14	PBE	Percentage Bias Error	-0.149	-0.74
15	PAB	Percentage Additive Bias	0.021	0.643
16	PPB	Percentage Proportional Bias	5.456	2.296
17	MSE	Mean Squared Error	0.011	0.009
18	RMSE	Root Mean Squared Error	0.106	0.095
19	RRMSE	Relative Root Mean Squared Error	0.102	0.092
20	RSR	Root Mean Standard Deviation Ratio	1.636	1.81
21	iqRMSE	Inter-quartile Normalized Root Mean Squared Error	0.269	0.256
22	MLA	Mean Lack of Accuracy	0.001	0
23	MLP	Mean Lack of Precision	0.011	0.009
24	RMLA	Root Mean Lack of Accuracy	0.001	0
25	RMLP	Root Mean Lack of Precision	0.011	0.009
26	SB	Squared Bias	0	0
27	SDSD	Product of Standard Deviations	0.001	0
28	LCS	Lack of Correlation	0.011	0.009
29	PLA	Percentage Lack of Accuracy	5.478	2.939
30	PLP	Percentage Lack of Precision	94.522	97.061
31	Ue	Random error proportion	94.522	97.061
32	Uc	Lack of Consistency error proportion	5.456	2.296
33	Ub	Mean Bias error proportion	0.021	0.643
34	NSE	Nash and Sutcliffe's Model Efficiency	0.827	0.827
35	E1	Absolute Model Efficiency	0.623	0.602
36	Erel	Relative Model Efficiency	0.766	0.81
37	KGE	Kling-Gupta Model Efficiency	0.866	0.886
38	d	Index of Agreement	0.95	0.952
39	d1	Modified Index of Agreement	0.805	0.796
40	d1r	Refined Index of Agreement	0.812	0.801
41	RAC	Robinson's Agreement Coefficient	0.952	0.954
42	AC	Ji and Gallo's Agreement Coefficient	0.796	0.813
43	lambda	Duveiller's Lambda Coefficient	0.905	0.908
44	dcorr	Distance correlation	0.901	0.892
45	MIC	Maximal Information Coefficient	0.841	0.817

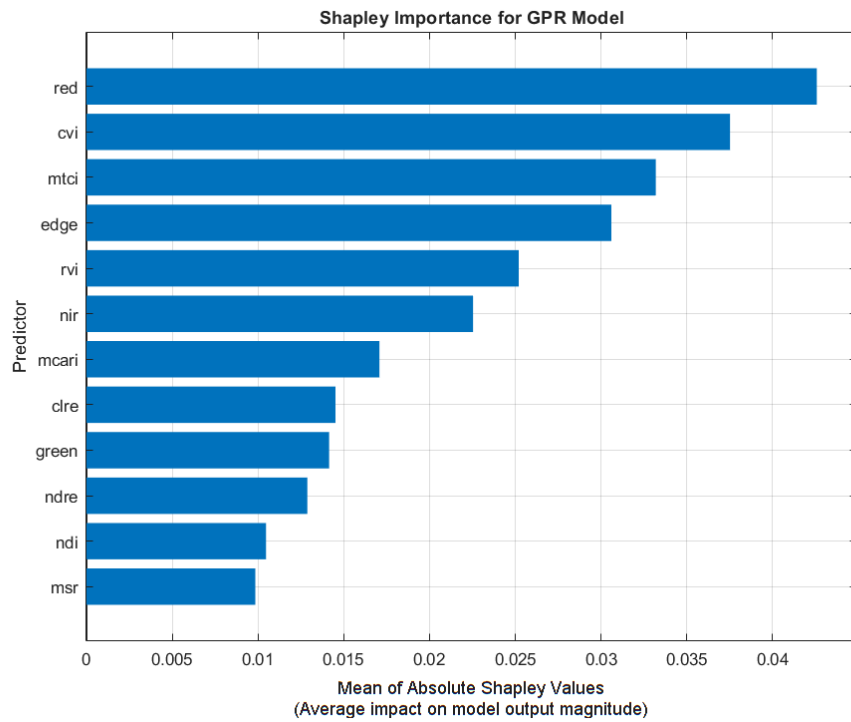


Fig. S1 Shapely predictors importance for GPR Model.

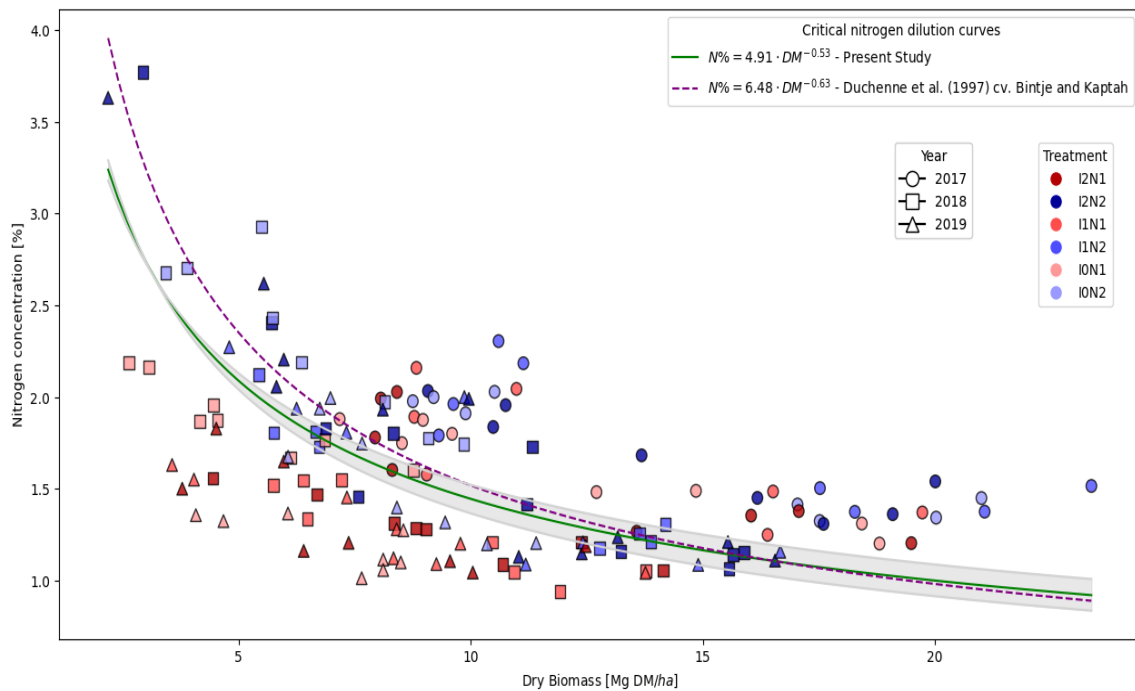


Fig. S2 Relationship between nitrogen concentration (%) and biomass (Mg DM/ha) for the potato cultivar 'Oleva' cultivated in Denmark. Points, square and triangles represent observed data respectively for 2017, 2018, 2019. The green curve and shaded confidence interval are the outputs of a Bayesian model. The purple dashed line represents the curve developed by Duchenne by cultivars Bintje and Kaptah (1997).

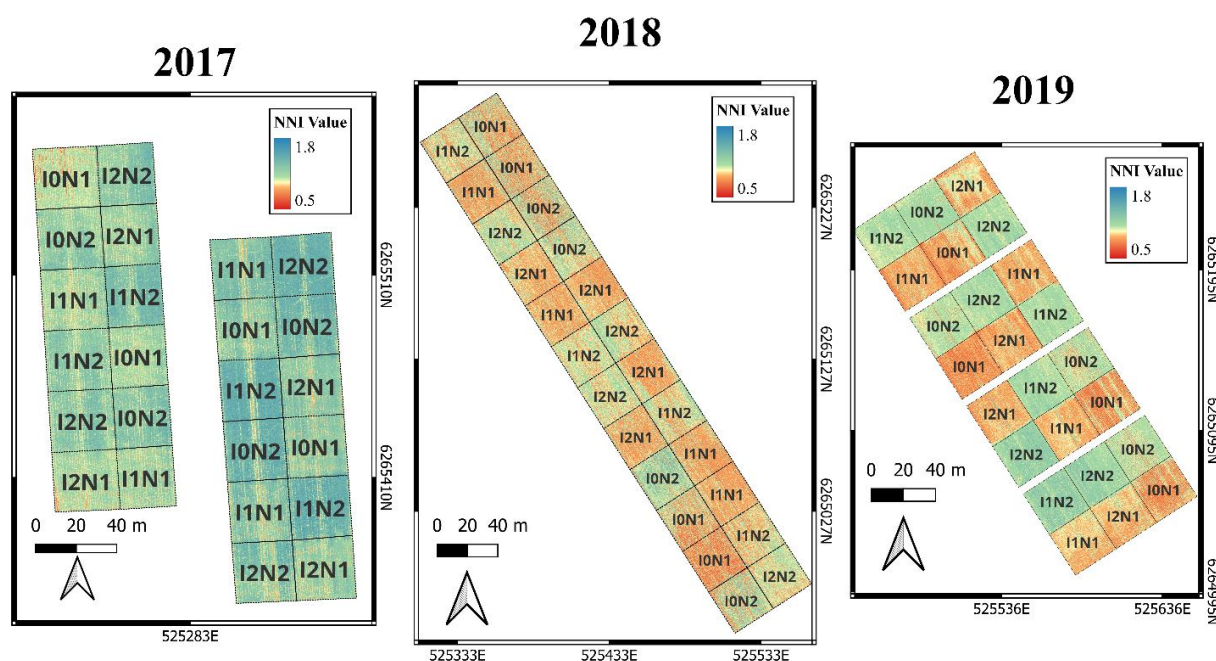


Fig.S3 Mid-season spatial distribution of NNI for potato crops in 2017 (17 July), 2018 (24 July), and 2019 (26 July). Maps are projected in ETRS89 / UTM Zone 32N (EPSG:25832).

Tab. S3: Summary of correlation results between predicted NNI and yield

Date	R^2
2017_07_13	0.5072
2017_07_19	0.6861
2017_08_23	0.2590
2018_05_11	0.0048
2018_05_31	0.0023
2018_06_07	0.0119
2018_06_22	0.4607
2018_06_29	0.1054
2018_07_04	0.2284
2018_07_11	0.0056
2018_07_19	0.0796
2018_07_24	0.0109
2018_08_01	0.0591
2018_08_08	0.3860
2018_08_16	0.4306
2018_08_21	0.0291
2018_08_31	0.0253
2018_09_02	0.1016
2018_09_05	0.3074
2019_05_31	0.0000
2019_06_06	0.0494
2019_06_27	0.3405

2019_07_05	0.6985
2019_07_10	0.3119
2019_07_18	0.2914
2019_07_26	0.4754
2019_08_14	0.4281
2019_09_18	0.5436

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Vineyard vegetative characteristics evaluation through UAV-based LiDAR SLAM technology

Abstract

Evaluation of vegetative characteristics is an important aspect in determining vineyard vigor. Traditional methods of evaluating these parameters are often time-consuming and labor-intensive. This study addresses the need for high-throughput phenotypic data by employing a UAV-based LiDAR system integrated with simultaneous localization and mapping (SLAM) technology. Experimental vineyards located in western Sicily were monitored during key phenological stages to determine vigor parameters. A DJI Matrice 350 equipped with a Hovermap ST-X LiDAR was flown over the experimental field. This system provides high-density point clouds with a detection range of up to 300 m and more than two million points per second with advanced SLAM technology for processing. Concurrent video capture with an action camera enabled RGB color assignment to the dense point cloud. Data processing was performed in Emesent Aura.

The resulting georeferenced 3D models effectively separated the vines from the background elements, allowing detailed partitioning of vineyard structures and vegetative parameters. Preliminary findings demonstrate the feasibility of using UAV-based LiDAR to accurately derive vegetative characteristics measurements, thereby reducing the problems derived from manual data collection. This approach offers a promising solution for vineyard management practices, improving the efficiency and precision of structural assessments. Overall, the proposed framework leverages advanced LiDAR-SLAM technology to provide robust phenotypic information, potentially advancing machine vision applications in viticulture.

Keywords: LiDAR, High-throughput phenotyping, UAV, Precision Agriculture.

Introduction

Viticulture represents one of the most relevant agricultural sectors in Italy, both economically and socially, and plays a pivotal role in global agriculture as well. The growing importance of vineyards has stimulated an intense research activity aimed at improving vineyard management,

with precision viticulture emerging as a key discipline. Precision agriculture addresses the challenge of producing more with fewer resources, while ensuring sustainability, by adhering to the “4R” principles: applying the right input, at the right time, in the right place, and in the right way. A central concept underpinning these principles is the identification and management of variability, which today represents one of the main goals of precision viticulture (Canicatti et al., 2025b). Variability in vineyards arises from the interactions among the different components of the agroecosystem, atmosphere, soil, and plant. Among plant-related parameters, vine vigor is particularly critical, as it directly affects the vegetative, reproductive balance, which in turn determines the delicate trade-off between yield and grape quality (Canicatti et al., 2025b, 2025a; Catania et al., 2025; Ferro and Catania, 2023). Several indicators have been proposed to quantify vigor, which can be broadly categorized into spectral and geometric parameters (Ferro et al., 2024). Spectral indicators, derived from canopy reflectance, allow the calculation of vegetation indices that capture physiological and structural differences in plants. Geometric parameters, such as Canopy Area (CA) and canopy volume, provide essential information for vineyard management, influencing practices such as pruning, irrigation, and disease control. The Leaf Area (LA) has proven to be fundamental variable for understanding canopy development, light interception, evapotranspiration, spraying treatments and ultimately irrigation requirements (Pagliai et al., 2024, 2022; Zarco-Tejada and Sepulcre Cantó, 2007). Traditional methods for estimating these vegetative parameters are often destructive, labor-intensive, and time-consuming, limiting their application to small scales. In this context, Light Detection and Ranging (LiDAR) technology has emerged as a promising alternative (Petrović et al., 2022; Tiwari et al., 2020). LiDAR is an active remote sensing technique that uses laser pulses to generate high-resolution three-dimensional representations of objects, enabling accurate and non-destructive characterization of plant structures. Its applications in agriculture are rapidly expanding, offering unprecedented opportunities for high-throughput phenotyping and precision crop monitoring (Canicatti and Vallone, 2024). While LiDAR has been successfully applied in several cropping systems, its application to viticulture remains relatively limited, despite the strong potential of this technology to improve vineyard characterization and management.

The present study aims to explore the use of UAV-mounted LiDAR for the estimation of vegetative parameters in vineyards. Specifically, we assess the capability of UAV-LiDAR data to extract structural features such as CA and LA, and we compare these estimates with conventional measurements. By integrating LiDAR-based geometric indicators into precision

viticulture, this research seeks to provide novel insights into vineyard monitoring and to highlight the potential of UAV-LiDAR as a high-throughput tool for sustainable vineyard management.

Materials and methods

Site location and experimental design

The experiment was conducted during the spring 2025 in an experimental vineyard field located in Sicily (Italy, latitude 37°51'53.45"N – longitude 12°57'15.71"E) at an altitude of 315 m a.s.l. and is drip irrigated. The terrain is slightly hilly, with slopes of approximately 12% on the steepest line. The layout of planting is 2.4 x 1.0 m (4170 plants ha⁻¹). The vines were trained on vertical trellises (VSP trellis system) and pruned using the double spurred cordon system with two buds per spur, spaced approximately 0.20 m apart.

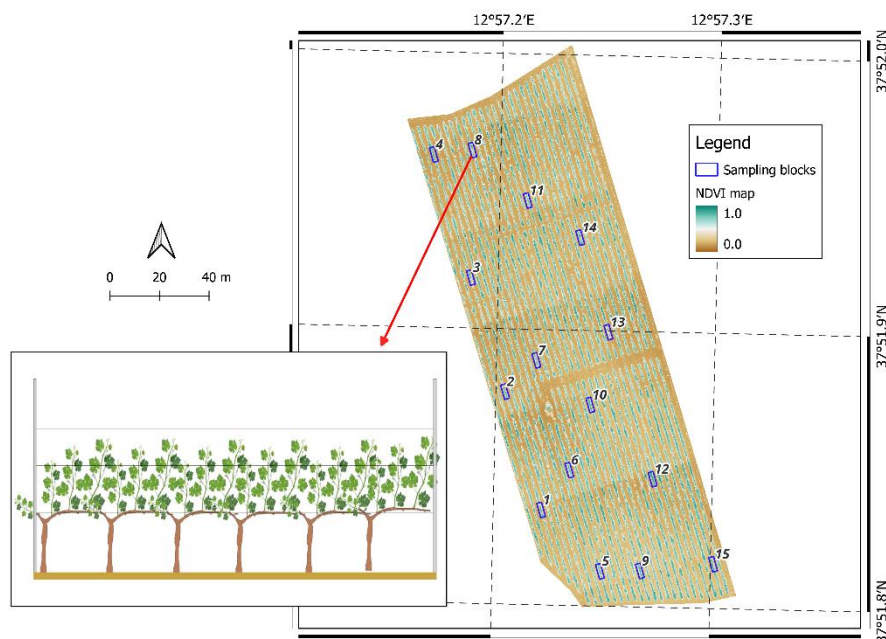


Figure 1. Experimental block localization

Ground Truth Measurements of Leaf Area

In the vineyard, 15 blocks of six meters in length were randomly selected, each containing six to seven vines. For each plant, several vegetative parameters directly related to vigor were recorded, including the number of nodes (buds left after winter pruning), the number and length of shoots, the number and length of suckers, and the number of inflorescences.

To obtain ground-truth measurements of the LA, thirty shoots were sampled across field areas with different vigor conditions. The shoots were collected from various positions along the fruit cane and included suckers. In the laboratory, all leaves were removed from the sampled shoots and arranged on a flat white background. Images were captured from a nadir position using an EOS 90D cam-era at 2 m and processed with ImageJ software to determine the number of leaves and the total leaf area per shoot (cm^2). The mean leaf area per shoot was then multiplied by the total number of vegetative shoots measured in the field, and the resulting value was divided by the number of plants per block to calculate the average leaf area per vine. All ground-truth measurements were carried out during the 2025 growing season, specifically on July 16 (DOY 197).

Remote sensing survey

Two remote sensing campaigns were conducted concurrently with the field vegetation survey on DOY 197: one for multispectral imagery and one for LiDAR acquisition.

Multispectral survey

The multispectral flight was performed using a DJI Mavic 3M platform equipped with four monochromatic bands in the spectral regions of Green ($560 \text{ nm} \pm 16$), Red ($650 \text{ nm} \pm 16$), RedEdge ($730 \text{ nm} \pm 16$), and NIR ($840 \text{ nm} \pm 16$), as well as an integrated RGB sensor. Data were acquired in RTK mode at an altitude of 80 m, with the camera-oriented nadir to the ground. Flight lines were planned diagonally to the row orientation to optimize photogrammetric reconstruction and ensure sufficient overlap among images. The survey was carried out under optimal environmental conditions, characterized by clear skies, high illumination, and low wind speed.

LiDAR survey

LiDAR data were collected using a DJI Matrice 350 carrying a Hovermap ST-X sensor (Emesent, Brisbane, Australia). This sensor integrates a 32-channel Li-DAR capable of acquiring up to 1.92 million points per second in multi-return mode, with an operational range of 300 m and an accuracy of approximately 15 mm under open-field conditions. The Hovermap ST-X is also equipped with the proprietary Wildcat SLAM technology, enabling real-time obstacle avoidance and autonomous operation in GPS-denied environments. The flight was performed at an altitude of 20 m, parallel to the vineyard rows. To ensure high point density, flight speed was maintained at 1.5 m/s.

Data processing

Photogrammetric workflow and GEOBIA

Multispectral images were processed following a standard Structure from Motion (SfM) pipeline to generate orthomosaics and digital surface models (DSM/DTM). A GEOBIA (Geographic Object-Based Image Analysis) approach was subsequently applied to automatically extract individual canopies through multiresolution segmentation and classification based on geometric and spectral features. For each object, spectral information (multispectral bands and derived vegetation indices) was extracted to characterize canopy condition and to discriminate vegetation from soil.

LiDAR analysis

LiDAR data were processed using AURA software, applying a maximum processing distance of 100 m during point cloud generation to improve accuracy. The resulting point cloud was managed in RStudio, where it was spatially clipped to block boundaries. Voxelization was then applied, generating cubes of 1 dm³. For each voxel, both the number of LiDAR points and the mean intensity value were extracted, enabling subsequent quantitative canopy analysis.

Results and discussions

Comparison Between Multispectral and LiDAR-Based Canopy Reconstructions

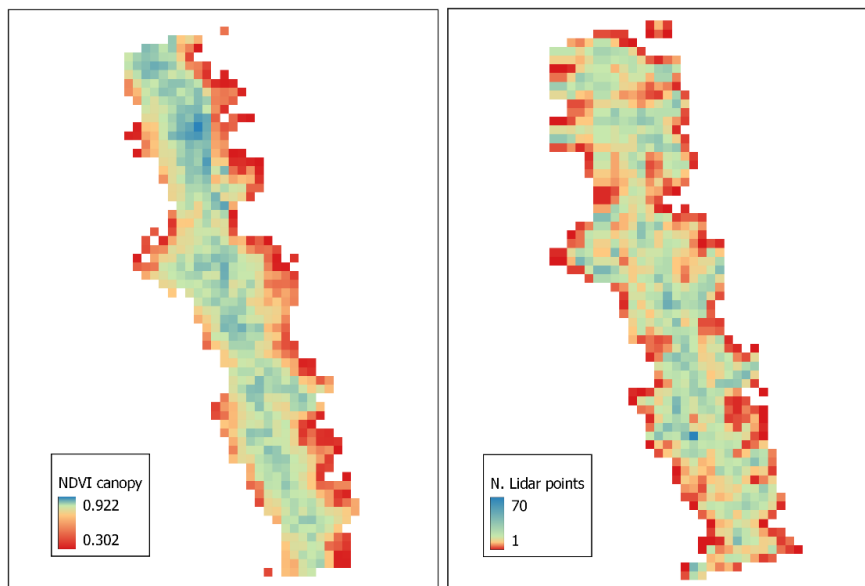


Figure 2. NDVI map (left), with values ranging from 0.302 (red) to 0.922 (blue), and Li-DAR point density map (right), with values ranging from 1 (red) to 70 (blue).

Figure 2 illustrates a comparison between canopy reconstructions obtained from multispectral photogrammetry (NDVI) and UAV-LiDAR data. Both approaches revealed a consistent spatial pattern, with higher values in the central portion of the canopy and lower values along the edges. However, some key differences emerged. The multispectral reconstruction was strongly influenced by illumination conditions, as evidenced by the asymmetric values caused by canopy shading. In contrast, the LiDAR-based reconstruction was unaffected by light conditions, providing a more uniform and geometrically robust representation of canopy structure. This highlights one of the main advantages of LiDAR technology in vineyard characterization, particularly under variable illumination scenarios that typically affect optical-based remote sensing.

The relationship between canopy metrics derived from the two approaches is further explored in Figure 3. A significant correlation ($R^2=0.67$) was observed between CA estimated through photogrammetry and the number of LiDAR points extracted per canopy. This correlation confirms the potential of LiDAR point density as a reliable proxy for canopy structural parameters. Although the relationship was not perfectly linear, likely due to canopy heterogeneity and the inherent differences in the measurement principles of the two sensors, the strength of the correlation demonstrates the complementarity of multispectral and LiDAR approaches. On one hand, spectral indices such as NDVI capture physiological variability, while on the other, LiDAR provides a more stable and illumination-independent estimation of structural parameters. Together, these findings reinforce the importance of integrating multispectral and LiDAR data to obtain a more comprehensive characterization of vineyard canopy variability, thereby enhancing the accuracy of precision viticulture applications.

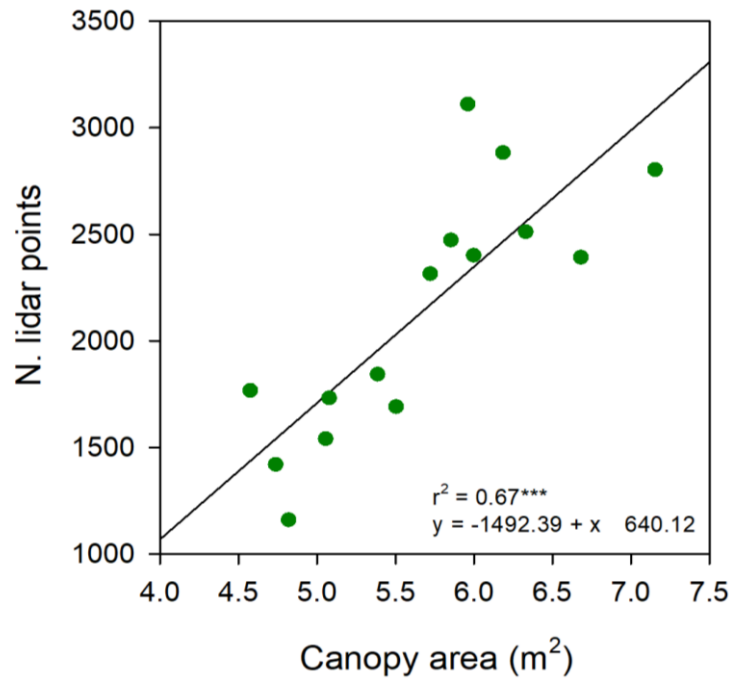


Figure 3. Relationship between CA (m²) and the number of LiDAR points.

Relationship Between UAV-LiDAR Metrics and Ground-Truth LA

Figure 4 presents the relationship between the number of LiDAR points extracted from canopy reconstruction and the LA measured from ground-truth data at both the individual plant (left) and block (right) scales. At the plant level, a positive correlation was observed, although with greater dispersion, reflecting the intrinsic variability in vine structure and the sensitivity of LiDAR to fine-scale heterogeneity. At the block level, the relationship was markedly stronger, with a nearly linear trend and reduced variability across observations. This result suggests that LiDAR based point density provides a robust proxy for canopy development, particularly when aggregated over larger spatial units.

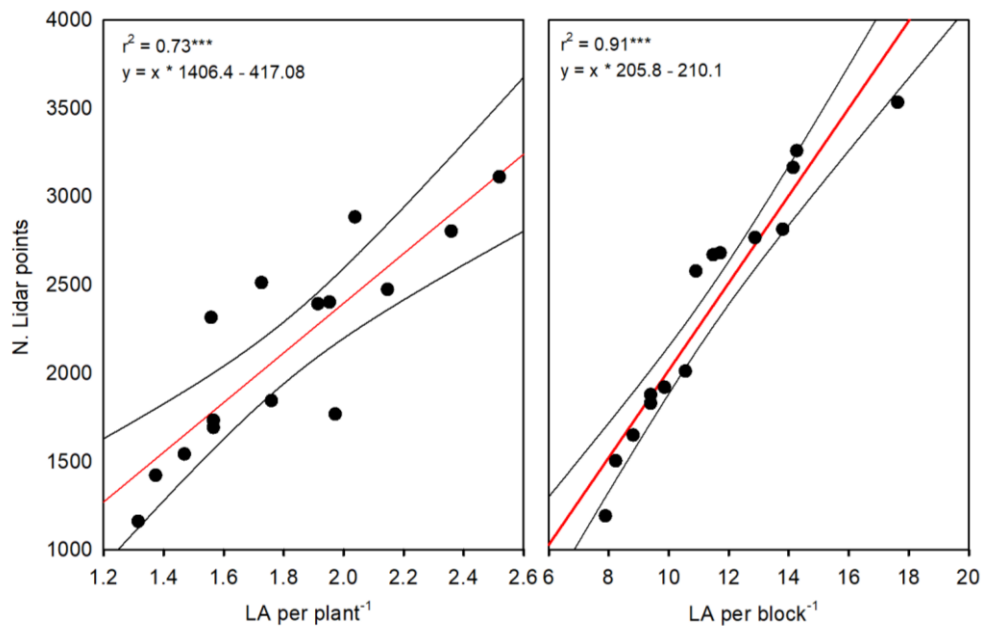


Figure 4. Relationship between the number of LiDAR points and LA derived from ground-truth data, at the plant level (left, LA per plant⁻¹) and block level (right, LA per block⁻¹). Black line indicates the 95% confidence intervals.

These findings are consistent with previous studies highlighting the capacity of LiDAR to capture three-dimensional canopy architecture and its strong potential as a non-destructive estimator of LA in different crops (Tiwari et al., 2020). Importantly, the reduced scatter at block level indicates that UAV-LiDAR can effectively minimize the influence of local micro-variability, providing reliable estimates of vegetation density for precision viticulture (Anastasiou et al., 2022; Gu et al., 2024). The integration of LiDAR-derived structural metrics with traditional ground-based measurements therefore offers a promising pathway toward high-throughput, scalable monitoring of vine vigor, ultimately supporting more accurate decision-making in vineyard management.

Conclusions

The integration of UAV-LiDAR and multispectral photogrammetry provided complementary insights into vineyard canopy characterization. While NDVI maps effectively captured spatial patterns of physiological variability, they were influenced by illumination effects, whereas LiDAR offered stable, light-independent structural reconstructions. The number of LiDAR points showed strong correlations with CA and LA, particularly at the block scale, confirming

its robustness as a proxy for vegetative parameters. These results demonstrate the potential of UAV-LiDAR as a high-throughput, non-destructive tool for quantifying vineyard canopy structure, supporting precision viticulture practices aimed at improving both productivity and sustainability.

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Spectral and thermal canopy characterization of different grapevine varieties

Abstract

Classification of vine varieties is essential for precision viticulture, as it enables the identification of distinct growth patterns and targeted management strategies based on the bio-agronomic characteristics of each variety. Remote and proximal sensors used in precision viticulture offer methods to assess growing conditions by exploiting hyperspectral, multispectral and thermal data collected in the field. This study aimed to assess spectral and thermal variations in the canopies of five grapevine varieties using both proximal and remote sensing techniques. The trial was conducted in the 2024 growing season in Sicily, Italy, in experimental fields where vineyards are managed according to ordinary practices of the area. Grapevine varieties examined were Catarratto, Grillo, Müller Thurgau, Pinot gris and Trebbiano Toscano, trained using vertical trellises and pruned using the Guyot technique. Multispectral data were acquired using the DJI Mavic UAV, while thermal data were provided by the sensor H20T mounted on the Matrice 350 UAV. The multispectral and thermal images were processed using Geographic Information System software to extract spectral and thermal features from canopies. Hyperspectral acquisitions were made with a FieldSpec® HandHeld 2™ spectroradiometer in sunlight canopy exposure. The hyperspectral data showed clear canopy signature differences of the examined varieties in specific spectrum regions. The multispectral data allowed to obtain continuous maps of crop variability, highlighting the vigor and health status of each variety. Thermal conditions were correlated with canopy area and vegetation reflectance.

Keywords: Remote sensing, Spectral signature, Phenotyping.

Introduction

The Eurasian grapevine (*Vitis vinifera* L.) is among the most widely cultivated and economically significant horticultural crops worldwide, with a history of cultivation dating back to antiquity (Galet, 1979). Detecting spectral differences among varieties thus offers valuable opportunities for scientific research and practical applications. Traditional approaches for grapevine varieties discrimination, such as ampelometry and DNA profiling, provide accurate results but are limited by high costs, time requirements, and the need for specialized analysis (Pelsy et al., 2010). Spectroscopy has emerged as a non-destructive alternative, with

studies demonstrating that grape varieties can be distinguished by their spectral signatures (Diago et al., 2013; Peñuelas et al., 1993).

Fewer studies have explored remote sensing explicitly for grapevine varieties differences. Satellite analyses indicated consistent spectral patterns especially in the near infrared that can support variety identification at parcel scale (Cemin and Ducati, 2011). Object-based satellite image analysis enabled accurate vineyard detection and parcel-level variety discrimination, supported by in situ spectroscopy that confirmed distinctive VNIR signatures for specific cultivars (Karakizi et al., 2016). At low altitude, UAV imaging has enabled fine-scale crop and vine canopy mapping (Ferro et al., 2023; López et al., 2024; Roma et al., 2023). UAV-based multispectral data have been widely employed in viticulture, mainly through vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which provides spatially explicit information on canopy vigor, nutrient status, and overall vineyard variability (Canicatti et al., 2025). These indices have proven effective in detecting inter and intra-varietal differences, especially when integrated with ground-truthing data (Catania et al., 2025). Likewise, thermal imagery has gained attention as a complementary tool, allowing the assessment of canopy temperature as a proxy for water status, stomatal conductance, and stress responses (Atencia Payares et al., 2023). When combined with multispectral information, thermal data enhances the capacity to characterize varietal-specific physiological traits and vineyard heterogeneity (Sims and Gamon, 2003). Spectral–spatial classification frameworks that combine clustering, model selection, and spatial regularization have outperformed conventional methods, underscoring the value of high-resolution imagery for vegetation analysis and class delineation (Senthilnath et al., 2017). Despite progress with spectroscopy, multispectral indices, and thermal imagery, integrated studies remain limited, and field evidence on their combined ability to discriminate grapevine varieties is still limited.

This study aimed to evaluate the spectral and thermal canopy variations of five grapevine varieties cultivated in Sicily by integrating proximal and UAV-based remote sensing. The overarching goal was to provide experimental evidence that supports varietal phenotyping and enables site-specific management practices within precision viticulture.

Materials and methods

Experimental field description

The study was conducted in 2024 in a vineyard located near Calatafimi Segesta (Trapani, Italy; 37°54' N, 12°51' E). The experimental site covers approximately 12.22 ha with a perimeter of about 1600 m (Figure 1, red area). The terrain is flat, with slopes below 5%, and characterized by a low percentage of coarse fragments. The soil moisture regime is classified as xeric, while the climatic conditions correspond to a thermic temperature regime. The vineyard is rainfed and managed according to local conventional practices. It consists of five white grapevine varieties: Pinot gris, Trebbiano Toscano, Müller Thurgau, Grillo, and Catarratto, all at the same stage of their perennial growth cycle (Figure 1). Training and pruning systems were equal across varieties, with vines grown on a vertical trellis position (VSP) under the Guyot pruning system. Planting distances were 2.2 m between rows and 0.8 m within the row.

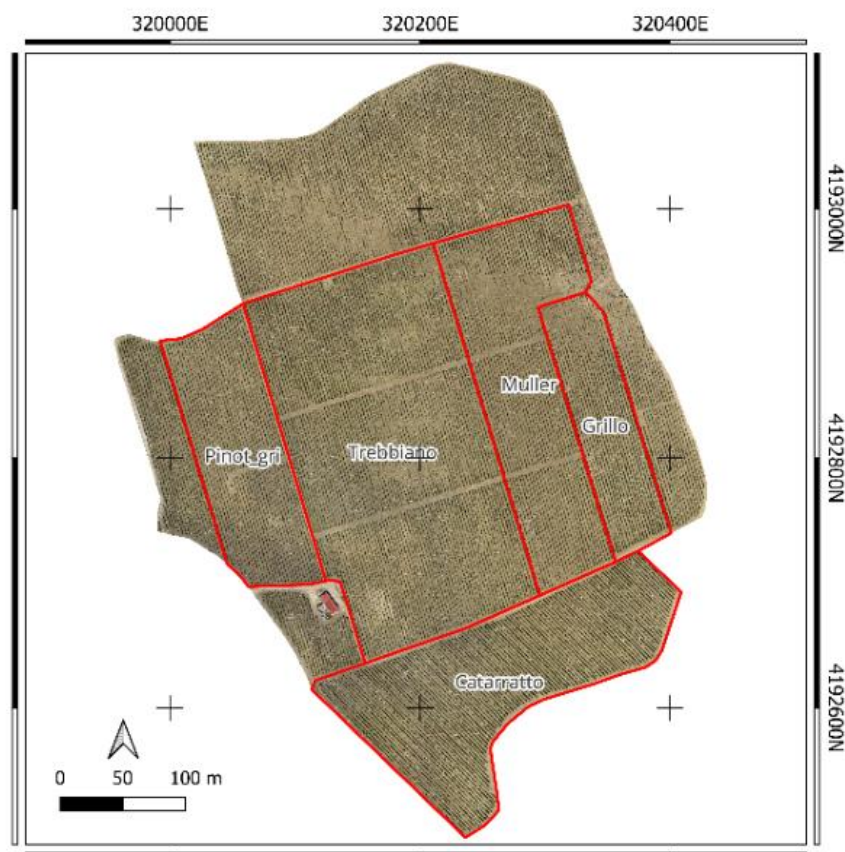


Fig. 1. Layout of the experimental vineyard showing the subdivision of the field into blocks corresponding to the five studied grapevine varieties.

Data acquisition

The field surveys were carried out on four acquisition dates, corresponding to DOY 120, 163, 197, and 232. These time points were selected to capture the main stages of the grapevine growth cycle, from flowering to berry ripening, thereby enabling continuous monitoring of canopy development throughout the season. Spectral and thermal data were acquired using two UAV platforms. The DJI Mavic 3M (SZ DJI Technology Co., Ltd., Shenzhen, China) was employed to collect multispectral imagery. The integrated camera includes five sensors: one 20 MP RGB sensor and four monochromatic sensors, Green (560 ± 16 nm), Red (650 ± 16 nm), Red Edge (730 ± 16 nm), and Near-Infrared (860 ± 26 nm), each with a resolution of 5 MP.

Thermal data were collected with the DJI Matrice 350 RTK quadcopter equipped with the Zenmuse H20T dual thermal–RGB camera. The thermal sensor provided a resolution of 640×512 pixels and operated within a temperature range of -40 °C to $+150$ °C. For both UAV platforms, autopilot flight plans were created in DJI Flight Planner to ensure systematic coverage. Images were acquired with 80% forward and side overlap at constant time intervals to maintain consistent ground sampling distance. Flights were conducted under optimal lighting conditions and low wind speeds, between 11:00 a.m. and 1:00 p.m., at an altitude of 70 m above ground level (a.g.l.).

All UAV imagery was processed using Agisoft Metashape Professional v. 2.0.2 (Agisoft LLC, St. Petersburg, Russia). The photogrammetric workflow comprised image alignment, dense point cloud generation, and the subsequent production of digital elevation model (DEM), and orthomosaic for each dataset. Thermal imagery was additionally processed with FLIR Tools to calibrate temperature and generate radiometric thermal maps. From these maps, the canopy–air temperature differential (ΔT) was calculated according to Eq. (1), where ΔT represents the difference between canopy temperature (T_c) and air temperature (T_a):

$$\Delta T = T_c - T_a \quad (1)$$

This parameter was used to quantify canopy temperature behavior relative to atmospheric conditions and to compare the physiological responses of the different grapevine varieties.

Final image analysis was performed in QGIS v. 3.16.6 Hannover (QGIS Development Team, 2021) using an Object-Based Image Analysis (OBIA) framework to classify vine canopies and extract quantitative vegetation metrics. From the multispectral imagery, the NDVI was derived and evaluated across grapevine genotypes to assess canopy vigor and spatial variability.

Hyperspectral data processing

Hyperspectral reflectance was acquired using a FieldSpec 2 spectroradiometer (ASD Inc., Boulder, CO, USA), operating in the 350–1000 nm range with 1.4 nm sampling interval. A Spectralon® white panel (Labsphere, NH, USA) was used for real-time calibration. Measurements were within two hours of solar noon, using a 25° FOV fiber positioned 40 cm above the top canopy leaves.

For each plant, five spectra were averaged into one representative measurement. A total of 15 sampling points per variety were sampled, with replicates across all five varieties. ASD binary files were converted into ASCII format using View-Spec Pro v6.20 and filtered to remove noise and water absorption bands. Data analysis was carried out in R v4.1.3.

Results and discussions

The results are presented in two main sections, focusing first on multispectral indices and then on thermal imagery, to highlight spatial variability and the response of different grapevine varieties within the experimental vineyard. Figure 2a illustrates the spatial distribution of NDVI across the experimental vineyard. Considerable intra-parcel variability was observed, reflecting differences in canopy vigor among and within varieties (Catania et al., 2025). Notably, Trebbiano Toscano and Grillo displayed higher NDVI, indicative of denser and more vigorous canopies, whereas Pinot gris and Müller Thurgau exhibited comparatively lower values, suggesting reduced vegetative development. The spatial patterns further highlight heterogeneity within individual blocks, underscoring the influence of both variety traits and local environmental conditions on canopy expression. Figure 2b presents the thermal map of the experimental vineyard, showing the distribution of canopy temperature across the different grapevine varieties.

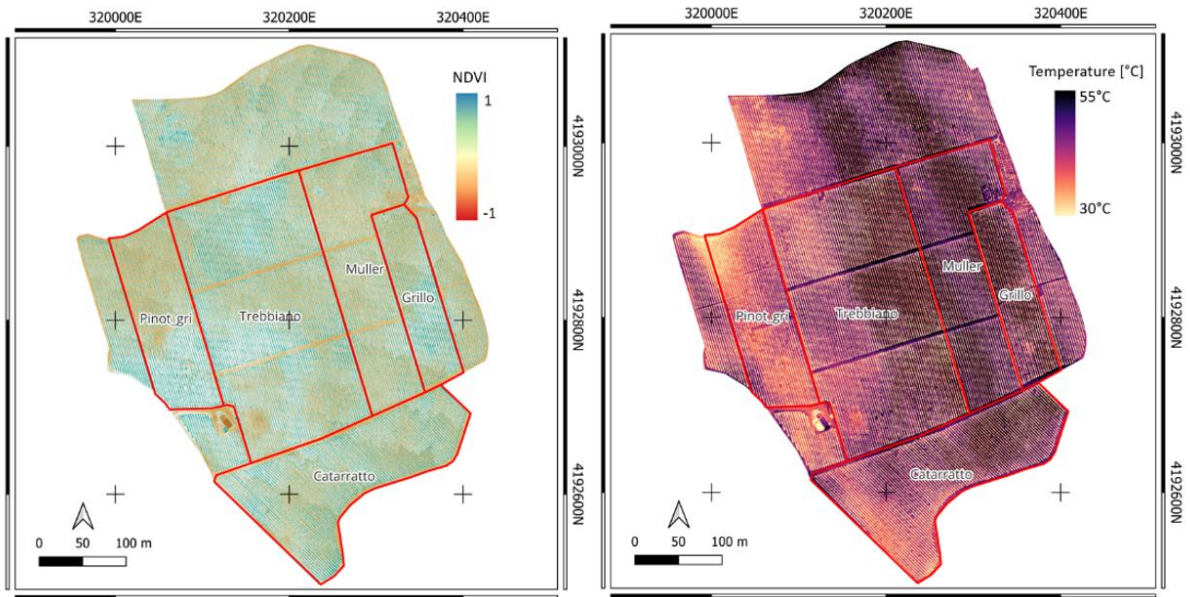


Fig. 2. (a) Spatial distribution of the NDVI across the experimental vineyard, highlighting variability among the five grapevine varieties. (b) Thermal map of the same vineyard showing canopy temperature distribution across varieties.

Figure 3 reports the temporal dynamics of NDVI across the five grapevine varieties during the 2024 growing season. For all varieties, NDVI values increased progressively from the early season (DOY 120) to a peak around mid-summer (DOY 200), followed by a decline approaching the late season (DOY 230). Among the varieties, Trebbiano Toscano and Grillo consistently exhibited higher NDVI values, indicating more vigorous canopy development. In contrast, Pinot gris maintained lower NDVI levels throughout the season, while Catarratto and Müller Thurgau showed intermediate values. The results highlight the greater suitability of the native cultivars, Grillo, Catarratto, as well as Trebbiano Toscano, which have retained higher NDVI during the period of intense vegetative growth. In contrast, the other varieties considered in this study showed lower NDVI, reflecting their trend to anticipate the growth cycle under the climatic conditions of this experimental area. This effect was particularly noticeable for Pinot gris, which showed lower canopy growth from mid-season compared to the other cultivars.

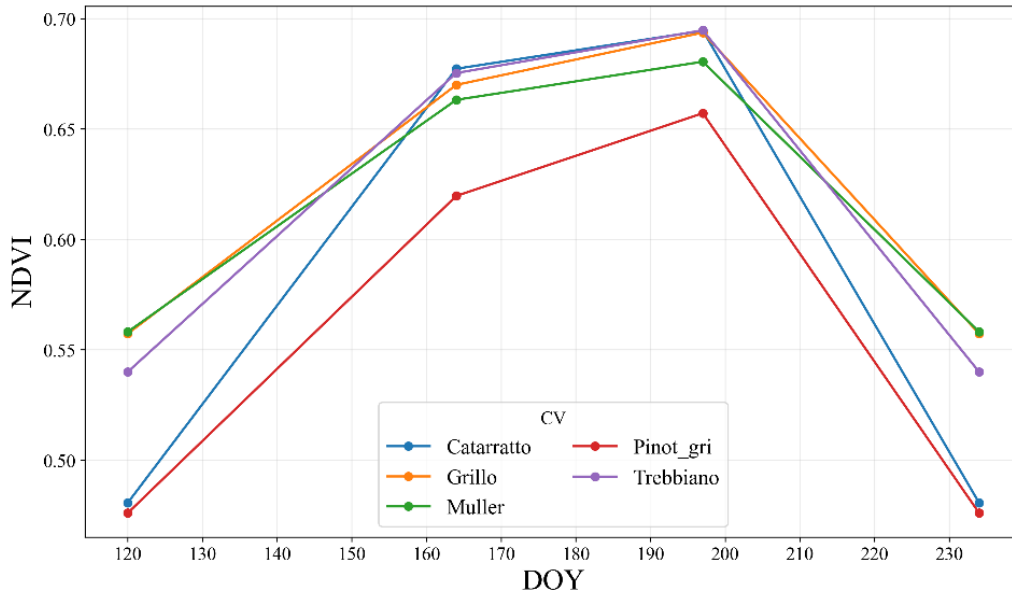


Fig. 3 Temporal evolution of NDVI in the five grapevine varieties during growing season, expressed as day of year (DOY).

Figure 4 shows the seasonal ΔT dynamics across the five grapevine varieties. Clear differences emerged among cultivars, with Pinot gris generally displaying higher ΔT values, while Grillo and Trebbiano Toscano maintained lower values during most of the season. When compared with NDVI trends, an inverse relationship was evident, varieties with higher canopy vigor, such as Grillo and Trebbiano Toscano, were associated with lower ΔT values, whereas Pinot gris, which exhibited reduced NDVI, showed consistently higher canopy temperatures. This correspondence highlights the consistency between spectral and thermal data in capturing differences in vegetative growth and physiological behavior among grapevine varieties (Atencia Payares et al., 2023).

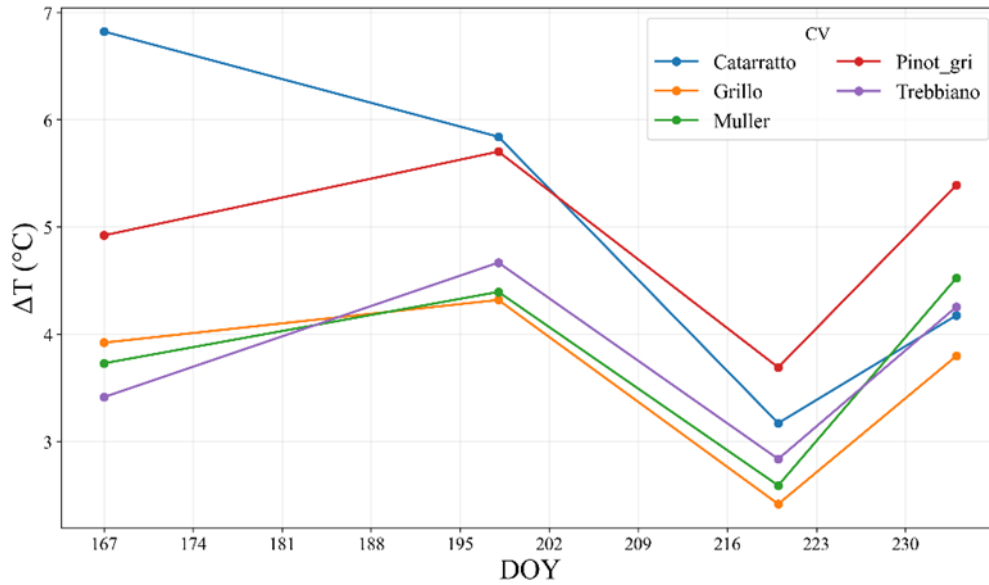


Fig. 4 Seasonal dynamics of canopy-air temperature differential ΔT [°C] across the five grapevine varieties, during growing season, expressed as day of year (DOY).

Figure 5 shows the hyperspectral reflectance curves (400-900 nm) of the five grape varieties. Clear differences emerged between the Pinot Grigio and Müller Thurgau varieties and the autochthonous varieties.

In the visible domain (400-700 nm), reflectance is mainly influenced by leaf pigments, which determine absorption peaks in the blue and red regions and the typical reflectance plateau in the green band (Peñuelas et al., 1993). Pinot Grigio showed relatively higher reflectance around 550 nm compared to the other varieties, suggesting differences in pigment composition and light absorption efficiency. In the near infrared (700-900 nm), reflectance is mainly determined by the structural characteristics of the leaves and their water content (Slaton et al., 2001). The literature indicates that NIR is among the spectral regions most strongly correlated with leaf water content (Sims and Gamon, 2003). In this regard, the distinct NIR signatures observed in Pinot Grigio and Müller Thurgau may reflect differences in leaf architecture and water use physiology, which are closely related to genotype and growth strategy.

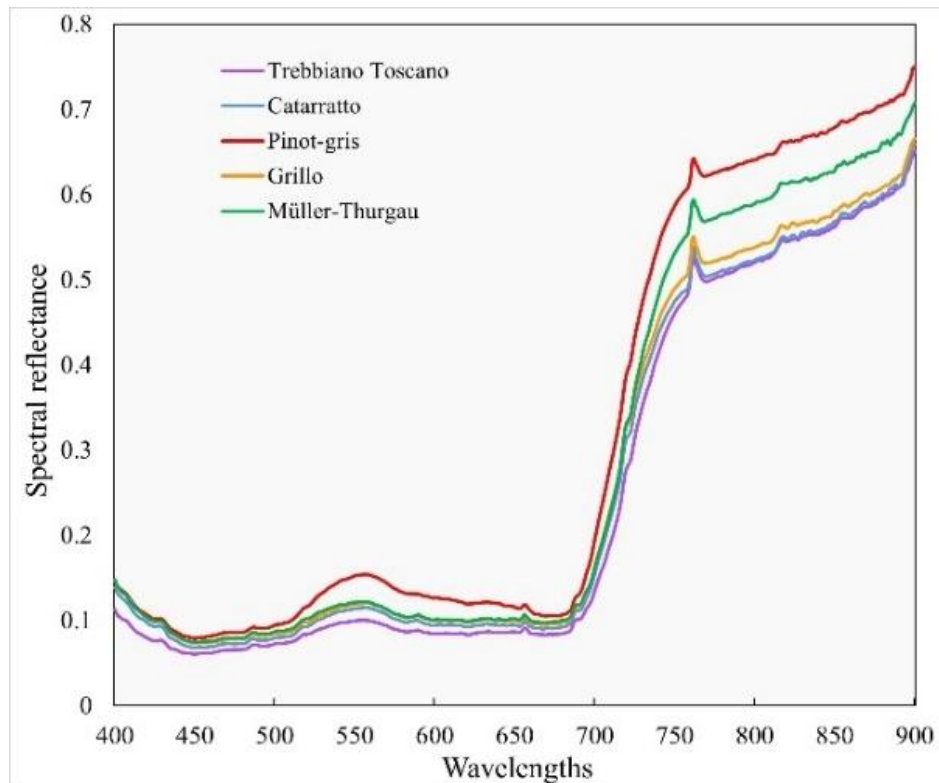


Fig. 5 Spectral signature (400–900 nm) of the five grapevine varieties.

This study demonstrates that integrating hyperspectral reflectance, NDVI mapping, and thermal imagery provides a comprehensive framework for characterizing grapevine varieties by capturing both structural and physiological traits. Such an approach advances the understanding of cultivar performance under field conditions and offers promising applications in variety identification and phenotyping, while future study should validate its robustness across broader genetic resources and diverse viticultural environments.

Conclusions

This study demonstrated the effectiveness of integrating NDVI, thermal, and hyperspectral data to assess canopy traits in grapevine varieties under Mediterranean conditions. NDVI and thermal mapping revealed consistent patterns of vigor and canopy temperature, while hyperspectral reflectance highlighted spectral differences, particularly between Pinot gris and Müller Thurgau compared with cultivar Grillo, Catarratto and Trebbiano Toscano. The results confirm the value of a multi-sensor approach for characterising varietal differences and assessing physiological responses, offering promising applications in precision viticulture and germplasm management.

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Olive tree canopy assessment by UAV multispectral images before and after pruning

Abstract

Precision olive growing applications have been increasing in recent years to manage spatial variability and achieve high quality and quantity. Pruning is one of the most important agronomic operations affecting plant vigour conditions. This study aims to provide a new approach for estimating the influence of pruning biomass on the vigour conditions, using multispectral images acquired by Unmanned Aerial Vehicle (UAV). The study was carried out in 2022 winter season, in an olive orchard located in western Sicily (Segesta, Italy). Multispectral images were acquired using a UAV Phantom 4 (DJI, China); in automatic flight configurations. Two flights were performed before (Day of Year 339) and after the pruning (DOY 364) with an altitude at 70 m a.g.l. generating a ground surface distance (GSD) of 3.6cm/pixel. Side over-lap and forward overlap were at 70%, flight paths were generated to minimize the time of flight, gimbal pitch was set at 90°. Starting from the Digital Elevation Model (DEM) and orthomosaic the Object-Based Image Analysis (OBIA) was applied. OBIA was used to perform canopy pixel segmentation from the soil and extract geometric and spectral canopy conditions. Pruning weight was measured in selected plants at the same time of the second flight. Correlation coefficients between geometric (canopy volume and area), vegetation indices (VIs) and pruning weight were calculated. VIs showed high correlation with canopy volume and area providing good prediction. The OBIA methodology demonstrated high accuracy in olive canopy reconstructions and detection in changes of vigour conditions. The trial provided interesting results to support olive growers to improve smart pruning management.

Keywords: Smart farming, UAV; vegetation indices.

Introduction

The farming techniques applied to olive cultivation are modifying in recent years with a growing emphasis on increasing the production efficiency while minimizing input and environmental sustainability (Godfray et al., 2010; Tilman et al., 2011). Olive cultivation is predominantly carried out in Europe within the Mediterranean region, particularly in countries like Spain, Italy, and Greece, which collectively account for 61% of the global olive cultivation area (FAOSTAT, n.d.). In these cultivation regions, different planting systems and agronomic techniques are applied. Moreover, the significant diversity in soil, climate, and crop conditions

leads to spatiotemporal variability in growth conditions that cannot be uniformly addressed (Connor et al., 2014; De Gennaro et al., 2012). This variability can be detected applying various technologies and sensors. In olive farming, some studies have indicated that the observed crop variability can be explained by knowing soil variability, especially organic matter, soil nitrogen and to some extent, electrical conductivity (Noori and Panda, 2016). Scientific research has focused on identifying biophysical (Sola-Guirado et al., 2017), spectral (Caruso et al., 2019; Roma et al., 2023a), and thermal (Agam et al., 2014) parameters to better understand vegetation growth and consequently productivity. Key biophysical parameters include canopy height, canopy area, canopy volume, and in some cases, perimeter and penetrability (Díaz-Varela et al., 2015; Sola-Guirado et al., 2017). Spectral parameters are based on observing the behavior of specific spectral bands and their combinations to calculate vegetation indices (VIs). The most widely used vegetation index in olive groves is the Normalized Difference Vegetation Index (NDVI) (Jhon W Rouse et al., 1974). NDVI provides a good indication of biomass, nutritional status, productivity, and physiological condition by utilizing reflectance in the red and near-infrared bands.

Precision agriculture relies on technologies capable of acquiring georeferenced information from various platforms to obtain diverse data for site-specific management of the agroecosystem. Among the remote acquisition platforms for detecting spatial and temporal variability, Unmanned Aerial Vehicles (UAVs) have been widely used within olive groves (Roma and Catania, 2022) thanks to their flexibility to be applied in different topographic and agricultural conditions.

Once variability within the olive grove is detected, various agronomic techniques can be applied for site-specific management, including irrigation (Ben-Gal et al., 2009), fertilization (Roma et al., 2023c), pest and disease control (Martinez-Guanter et al., 2020), and pruning (Jiménez-Brenes et al., 2017). Among these, pruning significantly affects management costs and often cannot be easily standardized (Ferguson et al., 2012). Pruning management is indeed closely tied to the experience of the farmers. However, precision agriculture is aimed at managing spatial-temporal variability to maximize plot efficiency. Pruning can modify canopy shape, affect the available resources, and influence vegetative activity and next year's productivity (Villalobos et al., 2006). Pruning management typically involves characterizing the tree architecture through manual measurements to describe the canopy geometry and estimate its

volume by applying empirical equations assuming the most similar shape (Miranda-Fuentes et al., 2015; Rosell and Sanz, 2012), this task being very time and cost-intensive.

Multispectral images from UAVs and image processing through Object-Based Image Analysis (OBIA) techniques can be used for monitoring the actual geometric and spectral conditions of crops at various levels of detail, down to each plant (Catania et al., 2023b; Jurado et al., 2020). The aim of this study was to study the influence of pruning operation on the vigor conditions of the olive trees using multispectral images acquired by Unmanned Aerial Vehicles (UAVs).

Materials and methods

Study area

The experimental area is located in Segesta (Italy; Figure 1), where the climate is classified as Mediterranean hot summer (Kottek et al., 2006).

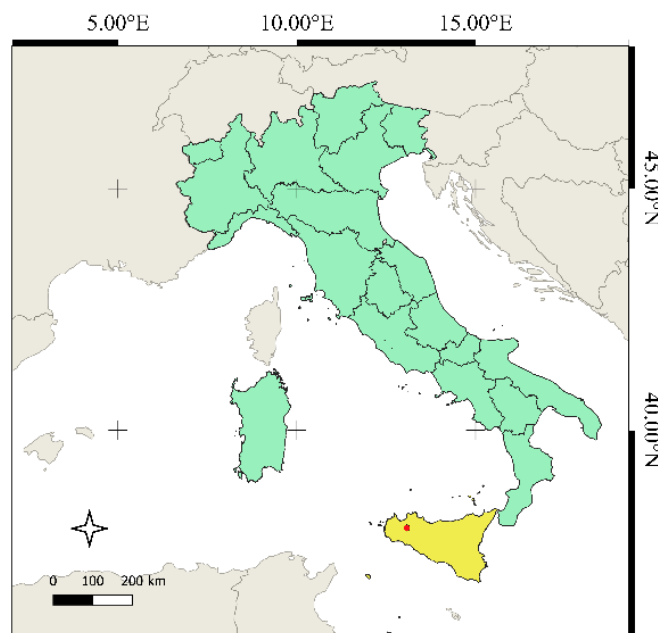


Fig 1. Experimental site location.

Soil belongs to the Sandy-Clay-Loam granulometric class, according to the United States Department of Agriculture (USDA) classification. The experiment was conducted in 2022 in a traditional training system twenty-year-old olive grove cultivated according to ordinary management practices. The total number of trees considered in the tests was 211.

UAV flights

Two flights were carried out in 2022 using a UAV platform equipped with a multispectral camera as described by (Roma et al., 2023c). The first flight was performed before pruning on DOY (Day OF Year) 339, the second after pruning on DOY 364. Flights have been planned using the official DJI software, setting the same main parameters. The flights were set with an altitude of 70 m a.g.l. generating a ground surface distance (GSD) of 3.6 cm pixel⁻¹. Side overlap and the forward overlap were at 70%, flight paths were generated by the software to minimize the time of flight, gimbal pitch was set at 90° (Downwards).

Before each flight, six Ground Control Points (GCPs) and the reflectance calibration panel were positioned to perform the geometric and radiometric calibration in the photogrammetric process, respectively. GCP were evenly placed at the edges and at the center of the plot on a solid platform and georeferenced using a GNSS instrument, specifically the Stonex S7-G (Milan, Italy) with external antenna and RTK correction (Catania et al., 2021, 2020a).

The flights were performed in excellent weather conditions with high light intensity and low wind speed at 12 noon. They were carried out with the automatic flight configuration following the predetermined routes and waypoints. The image acquisition was carried out at an average speed of 25 m s⁻¹.

Sampling and Surveys

During the test, 17 selected plants were sampled to collect vegetative, productive and spectral characteristics.

In correspondence of flight 1, for each selected plant the following parameters were evaluated: canopy height (CH) and canopy size in two directions (North-South and East-West). During the winter period, on DOY 350, all plants underwent intensive pruning operation. For each selected plant, the pruning biomass weight was evaluated using a digital dynamometer (Zetalab HCB 20K10, Padova, Italy) to evaluate the pruning operation effect on the vegetative and biometric parameters.

Images processing

Once the multispectral and RGB images were acquired, they were processed in order to obtain the multi-bands orthomosaic, the Digital Elevation Model (DEM) and the Digital Terrain Model (DTM) using Agisoft Metashape Professional (version 1.7.3) and analyzed through the open-source software QGIS (ver. 3.16.6, Hannover) (Blaschke, 2010; “QGIS Geographic Information System,” 2022). The details of the photogrammetric and OBIA process to obtain the spectral and biometric information for each plant are described in (Catania et al., 2023b). NDVI was used as vegetation index to determine the spectral variability and perform the classification process (Jhon W Rouse et al., 1974). Once individual canopies were extracted, they were classified into high (HV), medium (MV), and low (LV) vigor based on their NDVI and CA (Canopy area) values before pruning using a cluster analysis. This allowed for the assessment of spectral and geometric changes in the canopies for each vigor level.

Statistical Analysis

The data collected from sampling, ground survey and remote sensing platform were processed and statistically analyzed. Descriptive statistical analysis, accuracy of coefficient of determination (R^2) and root means square error (RMSE) index were calculated. The analysis of variance (ANOVA) and Tukey's multiple comparison tests were applied. All the statistical procedures were performed using R software (RStudio Team., 2015).

Results and discussions

The technologies applied to detect spatial variability showed an excellent ability to estimate the main vigour conditions (Figure 2). Specifically, the best results were obtained for CA estimation, showing a low RMSE value and high Pearson coefficients as also observed in other studies (Caruso et al., 2019; Catania et al., 2023b; Torres-Sánchez et al., 2015).

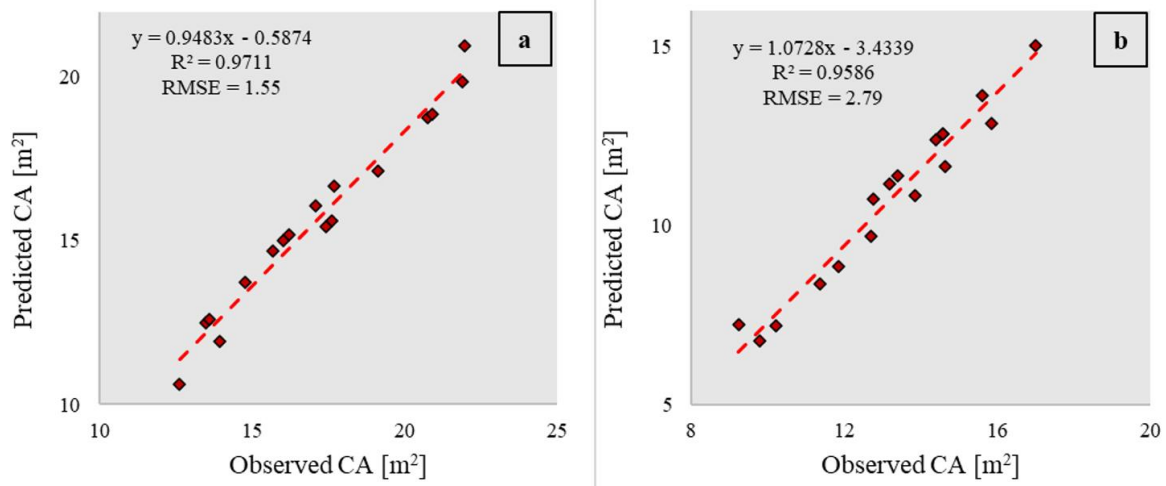


Fig. 2. Comparison between observed (ground) and predicted (UAV-estimated) values of the canopy area (CA), before (a) and after (b) pruning operation.

However, after pruning, a decreased in the estimation capacity is observed, probably related to the smaller size and higher biomass concentration of the plants (Catania et al., 2023b; Safonova et al., 2021). This leads to an overestimation of the ground data because the manual methodology is not able to quantify well the gaps created by pruning. Segmentation methods were also found to be less accurate, as there were more non-pure pixels than the whole CA (Jurado et al., 2020; Velázquez-Martí et al., 2011).

Olive orchard's vigour can influence its management. Therefore, its accurate evaluation is an essential element of site-specific management. In this experiment, the biometric conditions have been expressed in terms of CH, CA and CV (canopy volume) and showed a very important reduction after pruning depending on their vigour condition.

Before pruning, CH mean value was 3.57 m, while after pruning it was 2.91 m. Precisely, the three levels averaged 4.25 m, 3.57 m and 3.1 m from the highest to the lowest level of vigour before pruning; after pruning they decreased by 0.80 m on average.

CA was the vigour parameter that best correlated with spectral conditions and other vigour characteristics and showing high correlation with the production (Caruso et al., 2019; Sola-Guirado et al., 2017). UAV flight data allowed to estimate it underlining its reduction due to pruning. CA before pruning had an average value of 15.62 m²; it was reduced to 10.75 m² after pruning, showing an average decrease of 31.17% (Figure 3). This percentage ranged between 27 to 37% in the three vigour levels.

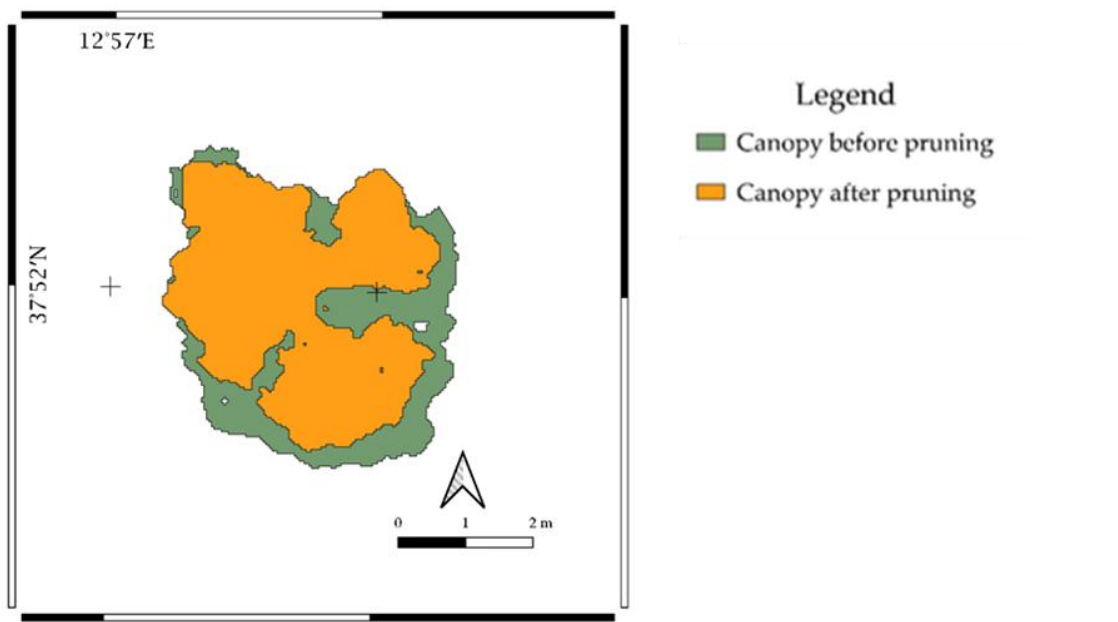


Fig. 3. Different shape of the canopy area of the sampling plant obtained by OBIA processing using orthomosaic.

Pruning operation also influenced the CV variation reducing it from 43 m³ to 26 m³ after pruning, showing an average reduction of 39.2% in the whole plot. These percentage values indicate high intensity pruning according to Jiménez-Brenes et al. (2017). The ANOVA confirmed that the amount removed from HV was statically higher than MV and LV ($p_{\text{value}} > 0.05$, Table 1). Furthermore, the biomass amount removed with pruning was good correlated with the volume before pruning, indicating that the amount of pruning removed per plant depends on the starting vigour conditions. Using the pruning weight data for the selected plants, it was observed that the removed biomass and the biomass density were statistically different in the three vigour conditions (Table 1). Indeed, the pruning density (kg m⁻³) showed that the biomass removed was homogeneous per vigour class while differences were observed between the classes (Table 1).

Table 2. Pruned volume and pruning biomass density obtained for each vigour level evaluated from GIS analysis ($p_{\text{value}} < 0.05$).

Vigour Level	Pruned volume	Pruning biomass density
	[kg]	[kg m ⁻³]
High	21.92 a	1.39 a
Medium	14.96 b	1.57 a
Low	12.31 b	0.70 b

The ANOVA showed statistically significant differences between the pruning density of HV and MV group compared to the LV group ($p_{\text{value}} = 0.05$). This can be related to the different amount of wood and leaves in the pruned material, as also found in other studies (Fernández-Escobar et al., 2015; Jiménez-Brenes et al., 2017).

Conclusions

The research provided an overview of the potential of remote sensing in olive groves for monitoring and estimation of vegetative, spectral and vigour condition due to pruning operation; in order to improve site-specific management. The study also highlighted that the estimation accuracy of these technologies is closely related to the vigor of the plants. Indeed, as the amount of biomass decreases, their performance reduces. Through this experimentation, it will be possible to accurately identify the plant conditions, enabling the implementation of variable-rate pruning operations, thus achieving advancements in automation and artificial intelligence.

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Section 4. Yield and biophysical parameters estimation

Bayesian yield mapping and uncertainty analysis in vineyards using remote sensing data and grape harvester tracking

Abstract

Yield mapping in viticulture is crucial for optimizing vineyard management. However, it remains constrained by limited yield monitoring sensors on grape harvesters and traditional remote sensing methods, which provide deterministic predictions without explicit uncertainty quantification. This study develops and evaluates a Bayesian hierarchical approach for vineyard yield mapping. The model integrates multi-sensor remote sensing and mechanical harvester telemetry data to generate high-resolution, uncertainty-aware yield maps at the farm scale.

Over two growing seasons (2022–2023) in a Sicilian vineyard. Normalized difference vegetation index data from unmanned aerial vehicles and Sentinel-2 satellites were combined with telemetry from global navigation satellite systems mounted on a mechanical grape

harvester. Multiple model configurations were systematically evaluated using the *brms* package in R, and sensitivity analyses were performed.

The best-performing model selected, based on six evaluation metrics (Bayesian R^2 , RMSE, MAE, MAPE, and ELPD), achieved an R^2 of 0.83 and RMSE of 0.26 kg/vine on training data, with independent validation showing an R^2 of 0.78 and RMSE of 0.09. The model effectively captured spatial and temporal yield variations. Specifically, it identified a 15% yield decline in 2023 linked to drought and heat stress, while explicitly quantifying prediction uncertainty.

This hierarchical Bayesian approach significantly advances vineyard yield mapping, demonstrating robust generalization potential. Integrating additional data from multiple seasons, different vineyards, and grape cultivars could further enhance predictive accuracy, reduce uncertainty in prediction and improve scalability of the framework. Ultimately, this methodology offers valuable insights for precision viticulture, supporting targeted agronomic management and informed operational decisions.

Keywords: UAVs, Bayesian modelling, Uncertainty quantification, Precision Viticulture, GNSS.

Introduction

Yield estimation is a central issue in agriculture, particularly within viticulture, as accurate estimations of production enable targeted agronomic management, aligning closely with desired oenological objectives. Traditional yield estimation methods in vineyards are often invasive, resource-intensive, and unreliable in capturing production variability due to the intrinsic heterogeneity of vineyard systems (Bramley and Hamilton, 2004; Fuente et al., 2015). Yield is composed primarily of two components at the plant level: cluster number per vine and average cluster weight (Komm and Moyer, 2015; Nuske et al., 2014). Grape cluster number is typically determined early in the vegetative season and is strongly influenced by vine vigor and fertility (Keller et al., 2010; López-García et al., 2022). Conversely, average cluster weight follows a double sigmoid growth curve, significantly influenced by environmental conditions such as average and maximum temperatures, accumulated growing degree days (GDD), and abiotic and biotic stresses (Lebon et al., 2008). Yield estimation, specifically termed yield mapping when incorporating spatial variability, involves direct yield assessment based on measurements taken within the production's temporal and spatial context (Maimaitiyiming et

al., 2019). This method is prominent in precision agriculture due to its capacity to capture spatial variability (Ping and Dobermann, 2005), distinguishing it from yield prediction or forecasting, which utilizes models based on data collected in earlier phenological stages (Laurent et al., 2021).

Yield mapping can employ sensors mounted on the harvester measuring harvested product indirectly, such as impact, pressure variation, or volume. While these systems are widely implemented in cereal cropping, grape harvesters rarely include these sensors, making yield mapping in viticulture more complex and less common (Colaço et al., 2020; Leroux et al., 2018). For instance, during mechanical harvesting, operator expertise significantly influences efficiency and damages to the vines, as optimal shaking frequency depend on canopy density and thickness, varying into the field conditions (Arfelli et al., 2010; Pezzi and Caprara, 2009). In this context, Gras et al., (2024) proposed an innovative, low-cost tracking method installed on harvest machines, correlating machine geolocation with winery-measured yield parameters.

Remote sensing (RS) technologies have emerged prominently in precision viticulture, offering non-destructive, extensive monitoring tools for vegetative state assessment and yield estimation and prediction (Hall et al., 2002; Towers et al., 2024). A common approach involves vegetation indices (VIs), calculates from different spectral bands, of which the most known is the Normalized Difference Vegetation Index (NDVI), closely correlated with leaf area and vegetative vigor (Campos et al., 2021; Ferro and Catania, 2023b; Johnson et al., 2003; Sun et al., 2017). NDVI effectively reflects leaf area dynamics influenced by phenological stages and agronomic practices, supporting interpretations related to the source-sink balance between leaf area and grape yield (Howell, 2001; Junges et al., 2019; Kliewer and Dokoozlian, 2005). Optimal NDVI values support balanced yield in terms of both cluster number and weight (Ohana-Levi et al., 2024). Satellite imagery, through its wide-area coverage, high revisit frequency, and cost-effectiveness, is increasingly central to vineyard yield prediction (Arab et al., 2021; Kamangir et al., 2024). Multi-source integration approaches, combining satellite with climate or agronomic data and proximal sensing, have further advanced these technologies (Anastasiou et al., 2018; Barriguinha et al., 2022; Canicatti et al., 2025b). However, limited spectral resolution of satellite imagery has led to an increasing interest for Unmanned Aerial Vehicles (UAVs), particularly advantageous in row-crop scenarios where soil background can impact measurements (Canicatti and Vallone, 2024; Ferro et al., 2024a). UAV platforms equipped with RGB and multispectral cameras offer high spatial resolution and flexibility in

temporal frequency, significantly benefiting vineyard variability analysis and yield estimation (Ferro et al., 2023; López-García et al., 2022). Additionally, canopy morphological features derived from UAV imagery, such as canopy thickness and volume, have demonstrated high predictive potential, although model generalization across seasons remains challenging, with tendencies toward overfitting and yield overestimation (Ballesteros et al., 2020; Matese and Di Gennaro, 2021; Šupčík et al., 2024). A systematic literature review conducted by Barriguinha et al., (2021) highlighted increasing interest in indirect, data-driven methods utilizing RS-derived VIs and computer vision technologies. Despite significant advancements and successful validation in experimental trials, widespread practical adoption remains limited, mainly due to methodological fragmentation.

Techniques involving agricultural machinery monitoring, remote sensing, and agro-environmental modeling often evolve independently, restricting synergistic applications. Frequent methodological limitations include reliance on simple frequentist models, like linear regressions, or machine learning algorithms that typically provide point predictions without adequately representing predictive uncertainty. Bayesian modeling presents a promising alternative due to its flexibility in integrating different data sources and explicitly quantifying uncertainty (Abbaszadeh et al., 2022). Unlike frequentist methods, Bayesian approaches formalize uncertainty via prior distributions updated by data evidence using Bayes' theorem, resulting in a posterior distribution more reflective of complex agricultural and environmental systems (Poudel et al., 2022; Veenman et al., 2024). Bayesian hierarchical models (BHM) are particularly effective, capturing data variability structured across multiple levels (e.g., years, experimental sites, crop varieties). Recent studies have demonstrated BHM's robust and generalizable predictive capacity due to explicit hierarchical relationship modeling (Bohman et al., 2023; Veenman et al., 2024). However, the application of Bayesian methods also presents significant computational challenges. These challenges often require the use of probabilistic sampling techniques, with Markov Chain Monte Carlo (MCMC) being the most widely adopted. MCMC enables the approximation of complex posterior distributions that cannot be derived analytically, thereby facilitating Bayesian inference in high-dimensional and non-linear models. Thanks to these sampling methods Bayesian models proven particularly effective in managing spatial variability within on-farm experimental settings as well as handling uncertainty in complex experimental designs characterized by sparse or unbalanced data (Cao et al., 2022; Cho et al., 2023). Additionally, Bayesian methods are increasingly applied to construct nitrogen dilution curves (CNDC), proving robust and flexible compared to frequentist

methods (Bohman et al., 2023; Makowski et al., 2020). Yield estimation and prediction also represent promising areas for the application of BHMs. Although still under development, growing body of research has demonstrated their effectiveness across a variety of cropping systems (Song et al., 2024). In particular, Bayesian frameworks have proven to be well suited for multi-source yield modeling, showing strong compatibility with heterogeneous and complex data sources such as remote sensing observations and process-based crop models. Applications have been reported for several important crops (Abbaszadeh et al., 2022; Lu et al., 2025; Roth et al., 2024). For instance, Ma et al., (2021) successfully applied BHMs to forecast maize yield using remote sensing variables, while Zhao et al., (2024) confirmed their suitability for cotton yield estimation. Bazrafshan et al., (2022) also highlighted the robustness of these approaches even in the presence of high climatic variability, further reinforcing their practical potential. In the case of wheat, Di et al. (2022) employed Bayesian optimization to improve yield prediction from remote sensing inputs, and Fei et al. (2023) adopted Bayesian model averaging to enhance the performance of machine learning models. Wu et al., (2022) demonstrated the potential of Bayesian inference for posterior yield prediction by integrating Sentinel-2 data into process-based crop growth models, effectively combining observational and mechanistic sources of information.

Despite recent advancements, a significant gap remains in the literature regarding the explicit application of Bayesian methodologies and predictive uncertainty quantification to vineyard yield estimation. In such systems, Bayesian modeling can serve as a highly valuable tool, given the high spatial variability and complex canopy structure typical of vineyards, which would particularly benefit from probabilistic frameworks capable of quantifying predictive uncertainty. To fill this gap, the present study introduces an innovative yield mapping framework based on BHM, which integrates heterogeneous and complementary data sources, including UAV and satellite multispectral imagery, field-based agronomic observations, and GNSS data collected during mechanical harvesting. The study's objectives are: (i) to build a Bayesian model for vineyard yield mapping, assessing the relative contribution of each input variable through a comprehensive sensitivity analysis; (ii) to validate the model against real field data obtained from harvest events tracked using GNSS-equipped harvesters; (iii) to analyze the spatial distribution of yield variability across the 2022 and 2023 seasons; and (iv) to evaluate the sources of predictive uncertainty through the field, identifying factors that increase or reduce confidence in model outputs.

Materials and methods

Data acquisition

Experimental field

The field experiment was conducted over the 2022 and 2023 growing seasons in a 15-year-old vineyard located within the Alcamo Protected Designation of Origin (PDO), in Sicily region, Italy. The site is geographically positioned at 37.92° N latitude and 13.07° E longitude, corresponding to the WGS 84 reference system (EPSG:4326) (Fig. 1). The field situated at 315 m a.s.l. and characterized by gently sloping terrain, with maximum gradients reaching 12%. The vineyard, extended in 8 ha, planted with *Vitis vinifera* L. cv. Catarratto, grafted onto 1103 Paulsen rootstock. Vines were trained to a vertical shoot positioning (VSP) system and pruned to a bilateral spur cordon with two buds per spur, spaced at 0.20 m. The planting design followed a 2.20×1.00 m layout, corresponding to a density of 4,545 vines ha⁻¹. The rows were oriented northeast–southwest, forming an angle of approximately 22° with respect to true north.

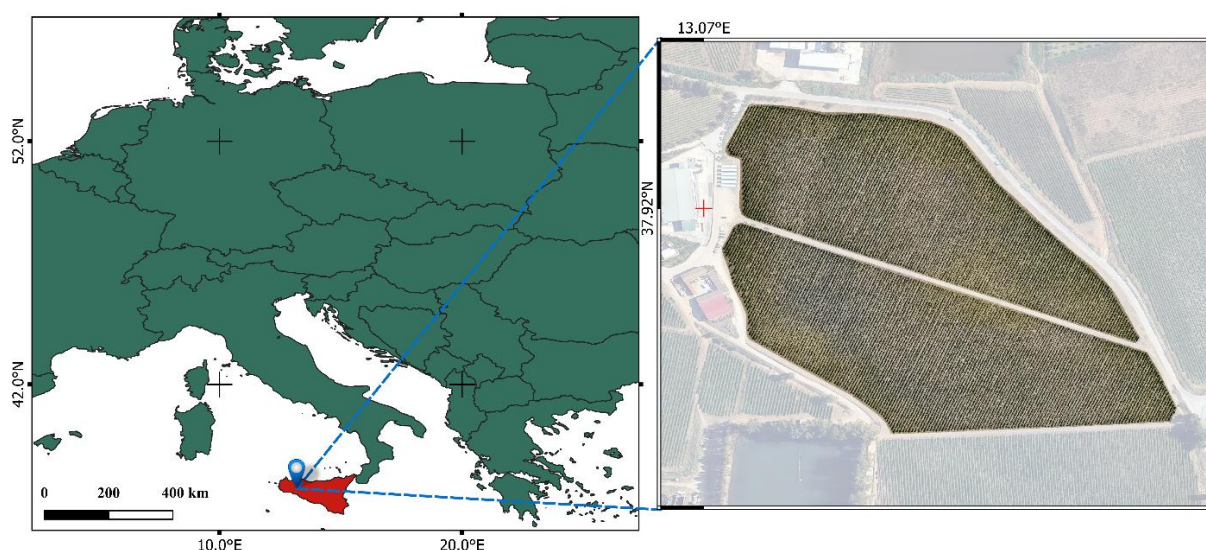


Fig. 1 Experimental field location (37.92°N; 13.07°E)

Vineyard management followed standard commercial practices applied uniformly across the field. Soil was managed through five shallow tillage operations (0.1 m depth) per year, aimed at weed control, reduction of surface evaporation, and prevention of soil cracking. Nutrient inputs and phytosanitary treatments were applied following regional guidelines to ensure healthy fruit production compliant with Alcamo PDO specifications. Drip irrigation was employed, with a seasonal water volume of approximately 600 m³ ha⁻¹. The study area was characterized by a Mediterranean climate, with mild, wet winters and hot, dry summers.

Historical climate data reported an average annual rainfall of ~650 mm, primarily concentrated between autumn and early spring. Weather data were collected with an EcoWitt WH6006 weather station placed near the experimental vineyard. The station was equipped with integrated sensors for measuring air temperature, relative humidity, rainfall, solar radiation, wind direction, and wind speed. Data were continuously acquired and automatically transmitted to a receiving unit for local storage and remote monitoring via GSM connection. The system operates autonomously thanks to an external solar panel. Average monthly temperatures during the March–August period ranged from 19 to 22°C. In 2022, seasonal weather conditions were near normal: cumulative rainfall for the first seven months reached 240 mm, and no significant anomalies were observed in distribution. Temperatures were slightly above average, with no extreme heat events. By contrast, 2023 exhibited a more irregular climatic pattern, with unusually high rainfall in May, followed by a prolonged dry spell and peak temperatures exceeding 40°C during summer.

UAV-based multispectral data

Multispectral data were acquired at harvest during the 2022 and 2023 growing seasons through two UAV surveys, conducted on August 28, 2022, and September 19, 2023, respectively. Flights were performed using a DJI Phantom 4 Multispectral (P4M; DJI Technology Co., China), a quadricopter platform equipped with six 1/2.9" CMOS sensors. The imaging system comprises one RGB camera for visible light acquisition and five monochrome sensors capturing distinct spectral bands: blue (B), green (G), red (R), red-edge (RE), and near-infrared (NIR). The system's field of view (FOV) was 51.50×41.25 m.

Prior to each flight, radiometric calibration was carried out using calibrated reflectance panel (LABSPHERE INC., North Sutton, US) to ensure consistent spectral response across acquisitions. UAV operations were conducted at 70 meters above ground level (a.g.l.) following a double-grid flight pattern with 70% overlap in both forward and lateral directions. The UAV maintained a ground speed of 6 m s^{-1} and acquired imagery at a frequency of 1 frame per second, with all images saved in uncompressed TIFF format. This configuration yielded a ground sampling distance (GSD) of approximately 37 mm for both RGB and multispectral images. Flights were planned between 11:30 and 13:30 local time to optimize illumination

conditions. Throughout the missions, weather conditions were stable, with high solar irradiance and low wind speeds, ensuring minimal atmospheric interference.

Post-processing was performed using Agisoft Metashape (Ver. 2.2.0) (Agisoft LLC, 2006), which was employed to generate high-resolution orthomosaics (GSD = 37 mm) obtaining a digitalization footprint of approximately 25 Mb/ha per band, in GeoTIFF format. For spatial analyses, all data were georeferenced to the EPSG:32633 coordinate reference system (WGS 84 / UTM zone 33N). To guarantee high positional accuracy, a network of 14 ground control points (GCPs) was distributed evenly across the study area and geolocated using a high-precision GNSS receiver, following the procedure described by Catania et al., (2020). Once the orthomosaics were aligned and corrected, vegetation indices were derived using QGIS software (version 3.22). Specifically, the Normalized Difference Vegetation Index (NDVI) was computed using the NIR (840 nm) and red (650 nm) bands (J. W. Rouse et al., 1974).

Satellite-based NDVI data

Multispectral satellite imagery was acquired from the Sentinel-2 platform and used to generate NDVI rasters over the experimental vineyard. Specifically, bands 04 (red) and 08 (near-infrared) were downloaded and employed as input for NDVI computation. The satellite data were provided by the Copernicus Programme of the European Union and retrieved via the Copernicus Open Access Hub (<https://copernicus.eu>).

To ensure consistency with the UAV acquisitions, the Sentinel-2 images closest in time to the UAV flight dates were selected. Only scenes with cloud cover below 10% were considered. Consequently, the Sentinel-2 imagery used in this study corresponded to August 28, 2022, and September 19, 2023, matching the UAV surveys. The final NDVI rasters were produced with a spatial resolution of approximately 7 meters per pixel and projected using the EPSG:32633 coordinate reference system (WGS 84 / UTM zone 33N).

Geolocalization of the harvester and shaker intensity mapping

Harvest operations were carried out using a mechanical grape harvester with a static shaker frequency. In such systems, the forward speed of the machine determines the number of shaker impulses delivered per linear meter of vine canopy. In the presence of spatial variability in

canopy density and structure, a fixed shaker frequency may result in suboptimal beating intensity across the field. This can lead to inefficient fruit detachment, increased plant damage, or fruit loss, unless compensated by appropriate speed adjustments. During field operations, the operator initially sets a fixed beating frequency and subsequently adjusts the machine speed in response to observed vine density. In this framework, machine speed acted as a proxy for the effective shaking intensity per length unit, indirectly modulated according to canopy structure.

During the 2022 and 2023 harvest seasons, mechanical harvesting operations were georeferenced using a STONEX S70G GNSS receiver (STONEX® Srl, Milan, Italy) mounted on the grape harvester. The unit features RTK correction and sub-centimetre accuracy, operating through the NMEA protocol with communication to up to 24 satellites, and provides horizontal accuracy of 0.5 m with positional updates at 1 Hz. The system, equipped with a magnetic base, continuously recorded position data. Data acquisition was performed on September 12–13, 2022, and September 28–29, 2023. The harvester interacted periodically with a trailer-pulling tractor for unloading. With a maximum capacity of 2,000 kg, grape transfer to the trailer occurred every time the maximum load was reached. Each grape filling event was documented by recording the start and end times of the operation. At the winery, the net weight of each trailer was measured, after subtracting the tare. To enable spatial analysis, the raw GNSS positional data, including the corresponding acquisition time, were exported as CSV files, then imported into QGIS (QGIS Development Team, 2023) and converted into shapefiles. The recorded start and end times of each filling event were used to classify and analyse the overall grape harvest process.

Only linear harvesting trajectories were retained, excluding turning paths. Each point represented a sampling unit associated with the variable Shaking intensity (impulse/m). To represent spatial variability in harvester shaker intensity, a geostatistical interpolation was performed using the SmartMap plugin in QGIS. Ordinary kriging was applied, with the semivariogram model automatically fitted to the data. The output consisted of a continuous raster surface (5 m resolution), exported in GeoTIFF format and georeferenced to the EPSG:32633 coordinate system (WGS 84 / UTM zone 33N).

Ground-truth yield measurements

To accurately characterize in-field variability, a structured and spatially informed sampling protocol was adopted. Identification of 18 sampling blocks was guided by a multitemporal analysis of intra-plot vegetative variability using remote sensing-based time series in combination with previous agronomic observations. The sampling strategy was based on the identification of temporally stable vigor zones derived from multitemporal remote sensing analysis and then validated through field inspections during key phenological stages (pre-veraison and ripening). This approach derives from previous studies conducted by Carrillo et al., (2016), in which applying this methodology improves the accuracy and spatial representativeness of yield sampling by targeting agronomically homogeneous sub-zones within the vineyard. Following this principle, the selected blocks were positioned to capture the spatial heterogeneity of the vineyard while maintaining operational feasibility within an on-farm experimental framework. Each block consisted of six vines, for a total of 108 georeferenced plants (Fig. 2), all mapped using a Real-Time Kinematic (RTK) GNSS receiver to ensure sub-centimetre positional accuracy.

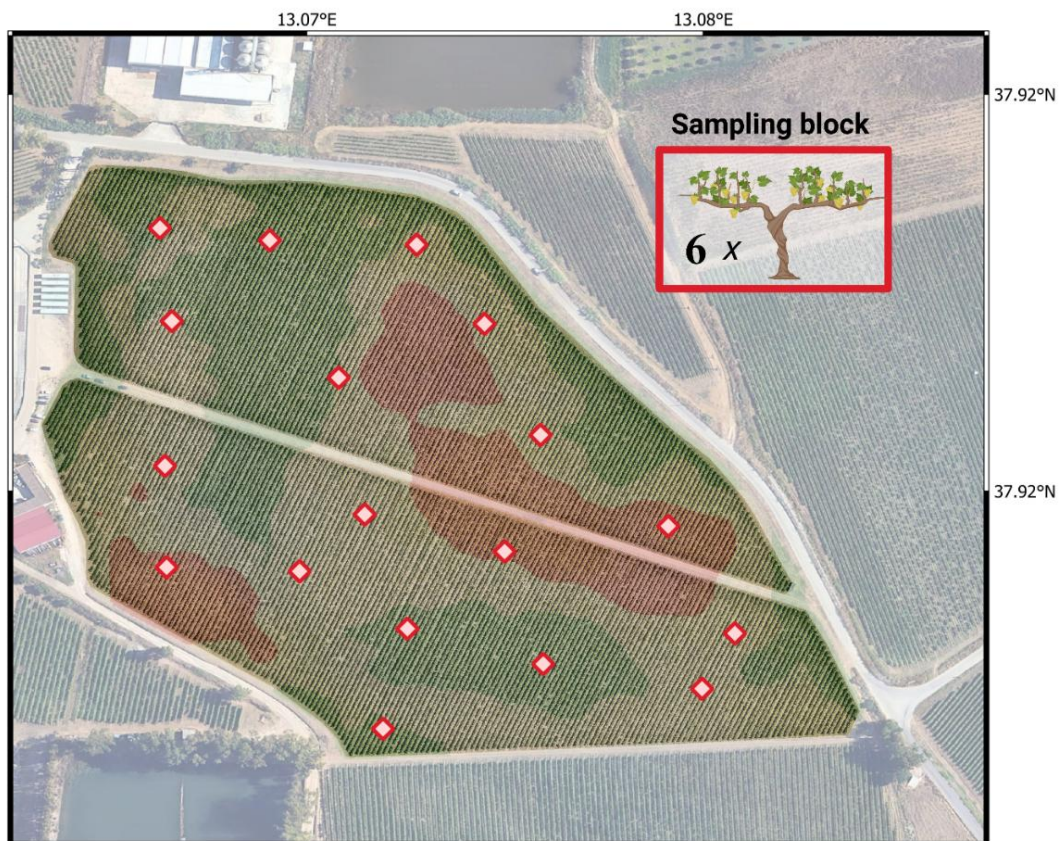


Fig. 2 Distribution of sampling block within the vineyard, each of 18 blocks consisting of 6 vines

At harvest, for each sampled vine, the number of grape clusters and the total yield per plant were recorded. The weight of individual clusters was determined using a precision scale (Wunder, mod. 60, Milan, Italy). The dataset obtained from this protocol, replicated over two growing seasons, provided a robust basis for model calibration and validation. This geospatial reference enabled the integration of yield observations with other data layers for subsequent analyses.

Multisource Data Fusion and Spatial Grid Definition

To accurately represent spatial variability within the vineyard, systematically support geostatistical analysis, and enable the integration of multi-source datasets, a georeferenced grid of observation units was created within the QGIS environment (QGIS Development Team, 2023). The entire process was designed to ensure maximum geometric accuracy and alignment with the actual vine layout in the field.

Using high-resolution UAV imagery as a spatial reference, a regular grid composed of rectangular polygons measuring 2×2 meters was defined. Each unit corresponds to two consecutive vines along a row, consistent with the actual planting scheme (Fig. 3e). The grid was initially generated for a single vine row and then replicated across all rows with consistent intra-row and inter-row spacing. Subsequently, it was rotated and translated to match the actual row orientation visible in the UAV imagery and the vineyard design layout.

After achieving precise spatial correspondence with the field geometry, the grid was refined by clipping it to the exact vineyard boundary. This operation excluded units falling outside the cultivated area or overlapping non-productive zones, such as headlands, row ends, or service paths. The refinement ensured that each spatial unit accurately reflected real agronomic conditions.

To enable efficient fusion of datasets from different sensors and characterized by diverse spatial resolutions and data structures, a standardized pre-processing pipeline was implemented. This procedure was uniformly applied to all input layers, including raster datasets derived from UAV-based imagery and Sentinel-2 satellite data, as well as data acquired from the grape harvester. Specifically, the zonal mean, defined as the arithmetic mean of all pixel values or points spatially crossing the grid unit, was calculated for each observation unit. This procedure made it possible to convert diverse spatial inputs into a single analytical resolution, ensuring that each

spatial unit maintained a representative and statistically uniform composition of the source data. All layers were reprojected and aligned to a unified coordinate reference system (EPSG:32633, WGS 84 / UTM zone 33N), ensuring geometric consistency of the entire multi-source dataset. Attribute tables associated with each grid unit were consolidated into a CSV format file. Raster data were aggregated over this grid using the zonal statistics tool in QGIS, computing the mean as the summary function for each unit. The final grid consisted of 17,083 georeferenced observation units, each treated as the minimum spatial element for data analysis and integration. The resulting attribute table, which contained all associated data layers referred to UAV, Sentinel, harvester and ground data, was then imported into R studio (R Core Team, 2024) for model training.

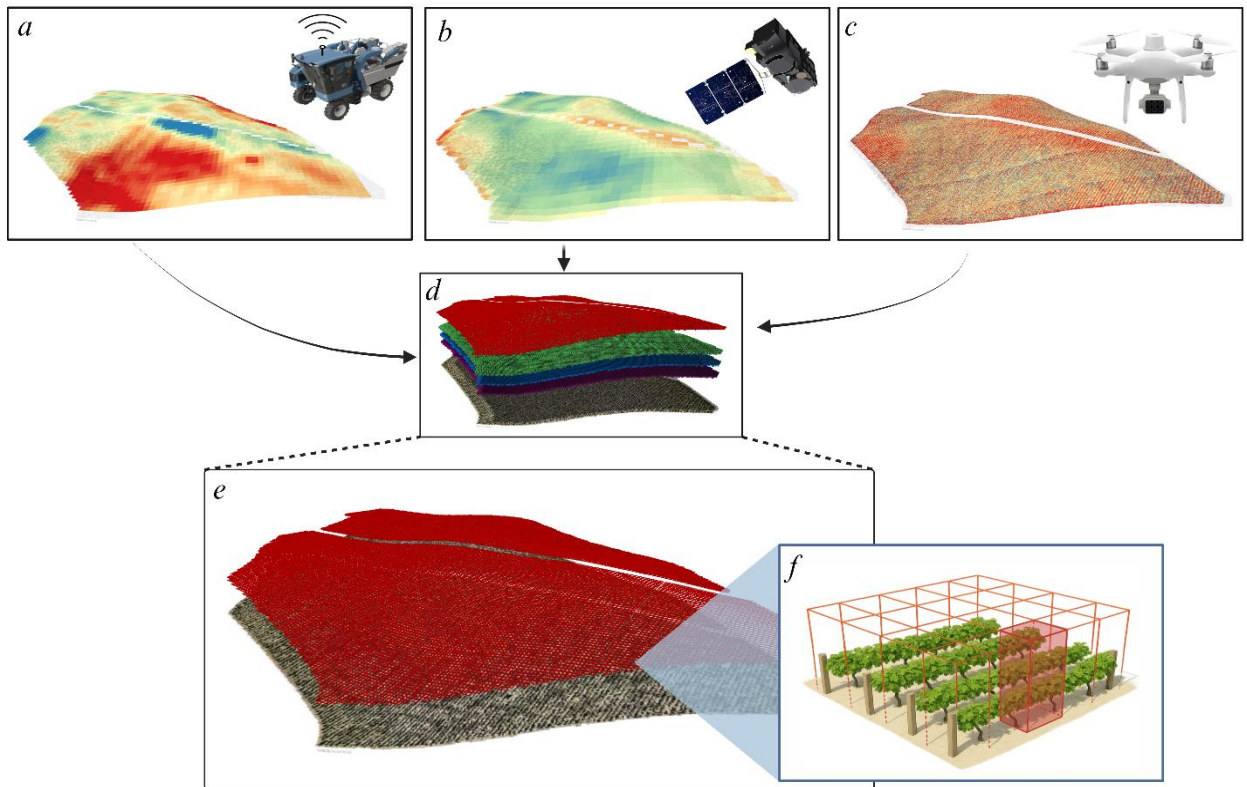


Fig. 3 Data structuring process; maps derived from the monitoring of mechanical harvesting operations (a), satellite imagery (b), and UAV-based surveys (c) were organized as informative layers and merged into a georeferenced grid (d) of observation units (f).

Model development and sensitivity analysis across alternative construction scenarios.

This study implemented a Bayesian inference model for vineyard-scale yield mapping, with the explicit aim of quantifying uncertainty associated with the predictive distribution of yield. The hierarchical Bayesian framework offers an intuitive and flexible approach for modeling complex, multilevel structures. It combines Bayesian inference with hierarchical modeling to account for both fixed and random effects, providing a robust and adaptable structure for a wide range of applications (Rouder and Lu, 2005).

The model training and evaluation was conducted in the R environment (R Core Team, 2024), using *brms* package (Bürkner, 2018, 2017), which serves as interface of Stan, a specific probabilistic programming language designed for Bayesian computation (Carpenter et al., 2017). The choice of *brms* was driven by its flexibility in specifying complex hierarchical models, including random effects, and its capacity to easily handle multi-source data. The sampling algorithm adopted by *brms* is Hamiltonian Monte Carlo (HMC), a gradient-based method that improves sampling efficiency and convergence over traditional MCMC algorithms (Ng'ombe and Lambert, 2021). In particular, the No-U-Turn Sampler (NUTS), a variant of HMC, is used in *brms* to automatically tune the sampling parameters and enhance convergence for models with high complexity (Bürkner, 2018, 2017; Carpenter et al., 2017).

The response variable modeled was the number of grape clusters per vine. To evaluate model behavior under varying configurations, several Bayesian model scenarios were developed and tested by changing both the covariate sets and the structural assumptions of the models. The predictor variables included NDVI derived from UAV imagery, NDVI from Sentinel-2 satellite data, and the mechanical harvester's shaker intensity per length unit, all of which were selected based on their relevance to yield prediction as supported by previous literature. The use of both UAV and Sentinel data allowed the model to benefit from the spatial detail of UAV observations and the temporal consistency of satellite data. Harvester speed was included as a GPS-derived metric that, under the assumption of a constant shaking frequency, served as a proxy for the number of shaking impulses per meter of vine canopy.

In the first phase, priors were carefully defined based on previous knowledge, exploratory analysis, and prior predictive checks. To ensure stability and realistic predictions, due to the lack of similar applications in literature, conservative weakly informative priors were adopted. Specifically, priors were set as follows: a Normal distribution centered at 0 with a standard

deviation of 1 was used for regression coefficients; the intercept followed a Normal (12, 1) distribution; the residual standard deviation was assigned a Student-t distribution with 3 degrees of freedom and mean 0; and the standard deviation of the random year effect was modelled with a Normal(0, 1) prior.

Sensitivity analysis was conducted by fitting the model under different experimental scenarios to explore how the model responds to structural changes and data configurations. In the first scenario, the effect of the hierarchical structure was assessed by comparing three pooling strategies across different years data: (i) total pooling, where data from multiple years were modeled jointly without accounting for year-specific variability; (ii) partial pooling, where a random intercept for the year was included to account for inter-annual effects (i.e. $(I | Year)$); and (iii) no pooling, in which separate models were fitted for each year independently.

The second scenario focused on the impact of sampling unit size. Two configurations were tested: Sampling Unit B, which corresponded to individual 2×2 m georeferenced observation units derived from the sampling grid described in 2.2 Section and represented two vines per unit; and Sampling Unit A, obtained by aggregating three adjacent observation units, thereby including six vines in total. This dual structure enabled the analysis of how different levels of spatial aggregation influence model training and outcomes.

The spatial dependency influence was evaluated in the third scenario. The inclusion of a spatial term was evaluated by incorporating a non-parametric smooth based on two-dimensional thin-plate splines over the sampling unit coordinates (i.e. $s(x, y)$). This spatial term was intended to capture residual spatial autocorrelation not explained by the fixed effects, thus potentially improving the model's predictive performance and spatial coherence.

Finally, a set of models was developed to assess the individual and combined contributions of the three predictor variables (UAV, Sentinel, Shaking intensity). Overall, a total of 112 Bayesian models were trained, all assuming a Gaussian error distribution. The models were run with four MCMC chains, each with 10,000 iterations, including 3,000 warm-up samples. Convergence was assessed by ensuring that all parameters had R-hat values below 1.01, and that both bulk effective sample size (bulk-ESS) and tail effective sample size (tail-ESS) were greater than or equal to 100 for each chain (Vehtari et al., 2021).

After model fitting, the posterior distributions of parameters were summarized by reporting the 0.05, 0.50, and 0.95 quantiles, thereby providing both the most probable estimates (median value) and their corresponding 90% credible intervals.

Evaluation criteria

The predictive performance of the models was assessed through a combination of Bayesian and frequentist metrics. From the Bayesian perspective, the model was evaluated on three main metrics: Bayesian R^2 and the Expected Log Predictive Density (ELPD), estimated through two cross-validation techniques. Bayesian R^2 quantifies the proportion of variance explained by the posterior predictive distribution, accounting for uncertainty inherent in Bayesian inference (Gelman et al., 2019). The ELPD was estimated using Leave-One-Out Cross-Validation (LOO) with Pareto-smoothed importance sampling (PSIS), via the `loo()` function in `brms`, which avoids repeated model fitting by approximating predictive accuracy efficiently. The process iteratively leaves out one observation at a time, using the remainder of the dataset for model training and the omitted point for validation. Alternatively, K-fold Cross-Validation, implemented through the `kfold()` function, partitions the dataset into k folds ($k = 10$), providing a robust estimate of predictive performance through repeated training and testing across subsets (Vehtari et al., 2017). In addition to Bayesian metrics, a set of standard frequentist error metrics was computed to provide an interpretable quantification of prediction accuracy. Specifically, the following metrics were calculated: RMSE [1] (Root Mean Square Error), MAE [2] (Mean Absolute Error) e MAPE [3] (Mean Absolute Percentage Error) according to classical definitions:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad [1]$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad [2]$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad [3]$$

Where y_i is the observed value, $\hat{y}_i$ is the predicted value and $\bar{y}$ is the mean of the observed value.

These frequentist metrics complement the Bayesian evaluation giving prediction error estimates that are widely used and easily interpretable.

Model accuracy evaluation and validation with ground-truth data

The simulation phase enabled the identification of the most informative feature combinations and model settings, resulting in improved predictive performance and robustness. Among all the configurations tested, the best-performing model selected for yield estimation was the following:

$$N^{\circ} \text{ Clusters} \sim \log(\text{UAV}) * \log(\text{Sentinel}) * \text{Shaking intensity} + s(x, y) + (1|\text{Year}) \quad [4]$$

Specifically, it employed a partially pooled hierarchical structure, accounting for interannual variability through a random intercept for the year (1|Year). It also included a parameter to consider spatial autocorrelation $s(x, y)$. The model was trained using data aggregated at the level of Sampling Unit A, which incorporated information from six vines per unit. Finally, it leveraged all three predictive features (UAV, Sentinel, Shaking intensity) demonstrating that the integration of multi-source and multi-scale data significantly contributed to model performance.

After model training, predicted and observed values were extracted and analyzed using the metrica plugin, an interactive web application build to interactive perform several performance metrics (Correndo et al., 2022). To assess the predictive capability and the model's ability to generate outputs with low error and minimal bias, a validation procedure was conducted using independent field data. Specifically, the total yield measured for each unloading area of the harvester was divided by the number of vines within that area, resulting in an average yield per vine. The model predictions, originally expressed as the number of grape clusters per vine, were then converted into yield (kg/vine) using the average cluster weight measured during harvest. A direct comparison between observed and predicted yield values for validation purposes was computed.

Spatial yield prediction and uncertainty analysis

Following validation, the model was used to generate spatial yield predictions across the entire field both the 2022 and 2023 seasons. The predictive variables associated with each georeferenced observation unit were extracted in tabular format and used as input for posterior prediction using the brms package in R. Since the model had been trained using 4 MCMC chains with 7,000 sampling iterations each, a total of 28,000 posterior samples were generated for each row in the new dataset. From the resulting posterior distributions, the median was used

as the most probable predicted value, while the 5th and 95th percentiles were extracted to define a 90% credible interval, representing the uncertainty associated with each prediction. The outputs were exported as .csv files and subsequently imported into QGIS for spatial visualization. This enabled the construction of detailed yield maps and corresponding uncertainty maps, providing a comprehensive view of the spatial variability in vineyard productivity across the two growing seasons.

Results

Model development and sensitivity analysis across alternative construction scenarios

Impact of pooling strategy on model performance

This first section of the results presents the accuracy metrics used to evaluate the predictive performance of the implemented models. The results of the simulation of the first scenario, aimed at assessing the impact of different pooling strategies on model robustness and predictive capacity, are summarized in Fig. 4. The figure illustrates how various pooling configurations influenced the overall model accuracy, highlighting clear differences in performance. This comparison allowed for the identification of the most effective approach in terms of predictive power and consistency, providing insights into the role of hierarchical structure in improving model generalizability across seasons.

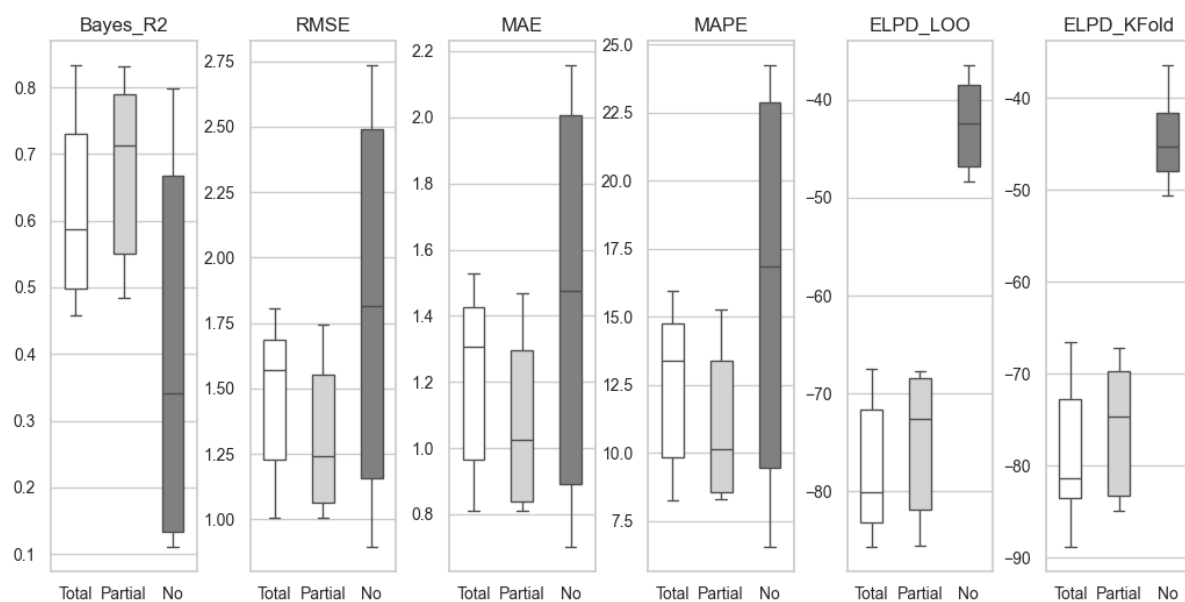


Fig. 4. Comparison among three Bayesian pooling strategies (Total, Partial, and No pooling) across six evaluation metrics: Bayesian R^2 , RMSE, MAE, MAPE, ELPD-LOO, and ELPD-KFold. The distribution of values derived from the simulated scenarios is represented through boxplots. The top, middle, and bottom edges of each box correspond to the 75th, median, and 25th percentiles. The line indicates the median value.

Models performance varied significantly depending on the pooling strategy adopted. The partial pooling approach consistently outperformed the others across most evaluation metrics. Notably, the Bayesian R^2 exhibited systematically higher values, with a median of approximately 0.7 and a maximum reaching 0.83, suggesting an enhanced capacity of the model to account for the variance in the observed data. Error metrics (RMSE, MAE, MAPE) further supported the superior performance of partial pooling, as evidenced by narrower distributions and lower mean values compared to total pooling. Indeed, partial pooling strategy exhibited the best performance in terms of RMSE, with a median value of approximately 1.25 and limited variability, as indicated by the interquartile range (IQR), which in this case ranged from 1.1 to 1.45. This result suggested greater accuracy and consistency across scenarios. In contrast, the total pooling approach yielded a slightly higher median (1.35) and greater variability. These differences became even more pronounced when compared to the no pooling strategy, which showed the poorest performance, characterized by markedly higher error values and a mean RMSE exceeding 1.75. In terms of MAE, the partial pooling strategy once again outperformed the others, yielding a median of approximately 1.0 and an IQR spanning from 0.85 to 1.2. The total pooling approach was associated with slightly higher error values, while the no pooling condition exhibited the poorest performance, with a median close to 1.5 and an IQR ranging from 1.0 to 2.0. Similarly, MAPE confirmed the same trend, with the partial pooling approach yielding the lowest median value (10.5%), followed by total pooling at 13.5%, and the no pooling condition exceeding 17.5%. The no pooling strategy also exhibited the widest spread, with upper quartile values surpassing 22.5%, which highlights its lower robustness and greater sensitivity to variability across groups.

Predictive accuracy metrics (ELPD-LOO and ELPD-KFold) showed more variable patterns. Interestingly, the No pooling strategy yielded less negative median values (around -45), suggesting better generalization to unseen data. Nevertheless, Partial pooling generally outperformed Total pooling in both ELPD-LOO and ELPD-KFold. Overall, the findings

indicate that partial pooling was the most effective strategy in this context, as it offered a balanced trade-off between flexibility and regularization, resulting in more accurate and stable predictions. Total pooling ranked second in performance, likely due to its tendency to over-constrain group effects and overlook relevant heterogeneity. In contrast, the absence of pooling leads to overfitting and a marked decline in both the estimation quality and the predictive capacity of the Bayesian model.

Impact of spatial structure of the data on model performance

The results presented in Fig. 5 focus on analyzing the impact of including spatial coordinates as explanatory variables on the performance of a BHM. The purpose of the analysis aimed to assess whether and to how effectively spatial information could improve model ability by providing a more accurate portrayal of the observed events.

In order to address this query, two separate scenarios were defined and compared. In the first, geo-coordinates were not included among the model covariates (scenario 0), while in the second, these were incorporated as explanatory variables (scenario 1). In both cases, the quality of the model was assessed using six different metrics.

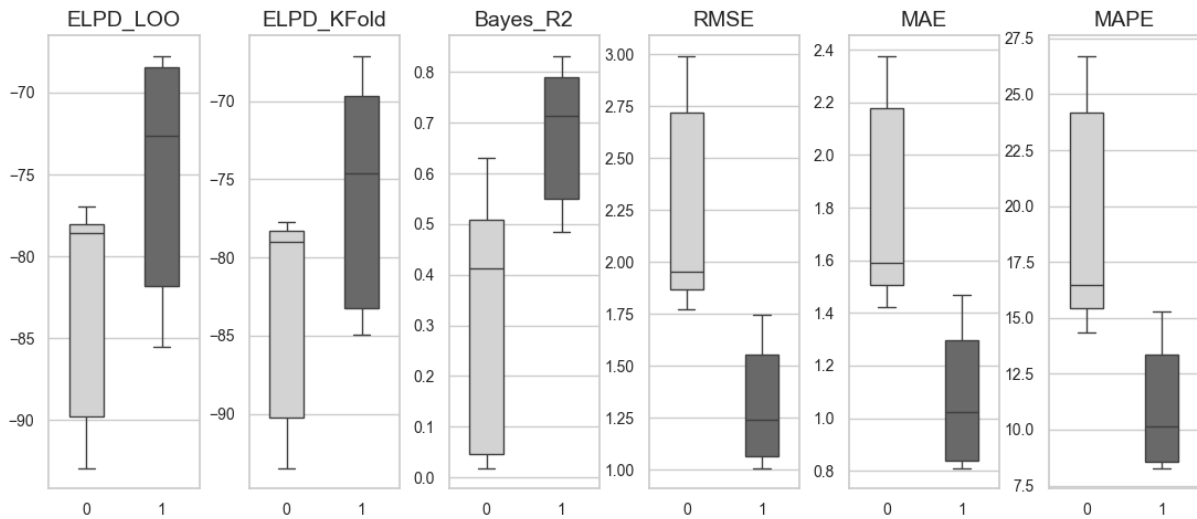


Fig. 5. Effect of the coordinates on BHMs performance, evaluated across six metrics: Bayesian R^2 , RMSE, MAE, MAPE, ELPD-LOO, and ELPD-KFold. Boxplots illustrate the distribution of values obtained from the simulated scenarios (0= no coordinates; 1=with coordinates). The top, middle, and bottom edges of each box correspond to the 75th, median, and 25th percentiles, respectively. The line denotes the median value.

Regarding predictive accuracy, both ELPD-LOO and ELPD-KFold showed less negative values than the control, indicating that the model incorporating coordinates generalized better to unseen data. For the ELPD-LOO, the median value increased from about -82 in scenario 0 to about -73 in scenario 1. Likewise, for the ELPD-KFold, the inclusion of coordinates resulted in an increase in the median value, up from about -82 in the scenario with no coordinates to -74 in the scenario with coordinates. The interquartile range reflected greater variability in scenario 1, though still associated with better performance. Similarly, the Bayesian R^2 metric was higher in Group 1 (with coordinates), reaching values above 0.8, which suggested a greater proportion of explained variance. In contrast, Group 0 (without coordinates) displayed much lower and more variable R^2 values, with some models explaining less than 20% of the variance.

Error-related metrics further confirmed the advantage of including spatial information: RMSE, MAE, and MAPE were significantly lower in Group 1, with tighter distributions and lower mean values. Specifically, RMSE and MAE fell below 1.5, reaching minimum values close to 1, and MAPE stabilizes below 15%. Conversely, Group 0 exhibited higher and more dispersed error values.

Overall, the results demonstrate that incorporating spatial coordinates had a consistently positive effect on all model evaluation metrics.

Impact of sample unit size on model performance

Fig. 6 presents the performance of a BHMs trained using two different sampling units (A and B), aiming to assess the effect of spatial resolution and data aggregation on predictive accuracy. Six statistical metrics were used for the comparison. Each boxplot summarizes the distribution of metric values obtained across multiple simulated scenarios.

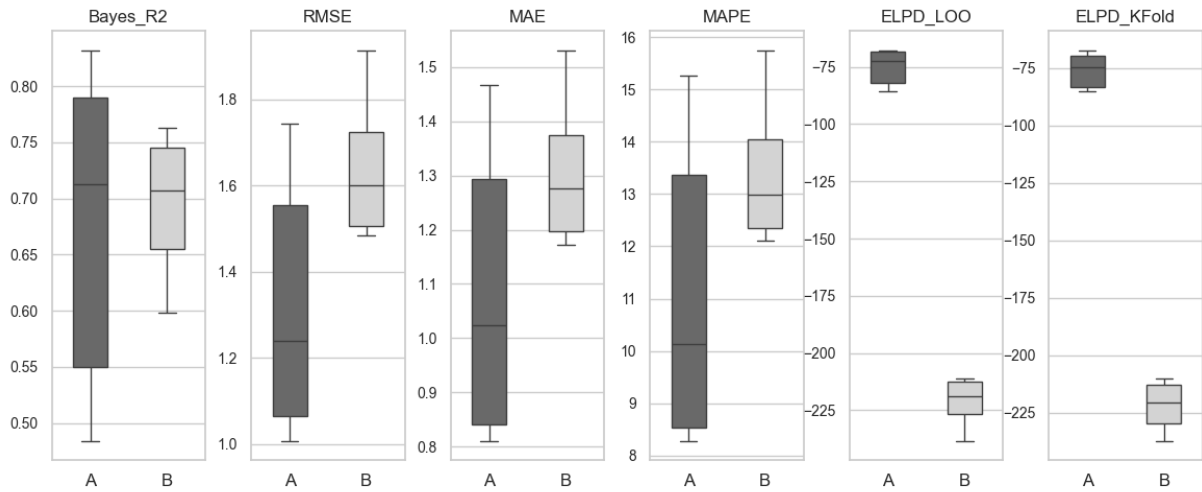


Fig. 6. Performance of a partially pooled Bayesian model trained using two different sampling units (A and B). The impact of sample unit size on model performance is evaluated across six metrics: Bayesian R^2 , RMSE, MAE, MAPE, ELPD-LOO, and ELPD-KFold. Boxplots illustrate the distribution of values obtained from the simulated scenarios. The top, middle, and bottom edges of each box correspond to the 75th, median, and 25th percentiles, respectively. The line denotes the median value.

These differences were particularly pronounced for the ELPD-LOO and ELPD-KFold metrics, where Sampling Unit A (A) significantly outperformed Sampling Unit B (B), with average scores above -75 for A, compared to approximately -225 for B. In addition, the IQR related to the ELPD-LOO metric was extremely narrow for unit A, while it is much wider for unit B (IQR about 30), suggesting greater reliability and explanatory robustness of the model associated with the unit of A. Similarly for the metric, ELPD-KFold a tighter IR was always observed for unit A than for unit B. Although less marked, notable differences were also observed in error-related metrics (RMSE, MAE, and MAPE), with model A consistently achieving lower values than model B. Specifically, the RMSE for model A was concentrated between 1.0 and 1.4, while model B ranges between 1.5 and 1.8. The MAE for model A was generally below 1.2, compared to values between 1.2 and 1.4 for model B. The MAPE for model A ranged from 8% to 14%, whereas model B presented higher values, with a narrower distribution between 12% and 15%. In terms of Bayesian R^2 , unit B showed a better model fit, with a median value of approximately 0.73. The interquartile range was significantly smaller for unit B (0.66-0.74) than for unit A (0.55-0.78), suggesting not only a better central fit but also greater stability between the simulated scenarios. On the other hand, sampling unit A, despite a slightly lower R^2 and higher variability in some metrics, consistently offered more accurate and robust performance, particularly when considering out-of-sample error estimates.

Relative features importance

Fig. 7 presents the results of the sensitivity analysis conducted to assess the relative importance of the three explanatory features used to train the BHM for yield mapping: Sentinel-derived NDVI, UAV-derived NDVI, and mechanical grape harvester Shaker intensity.

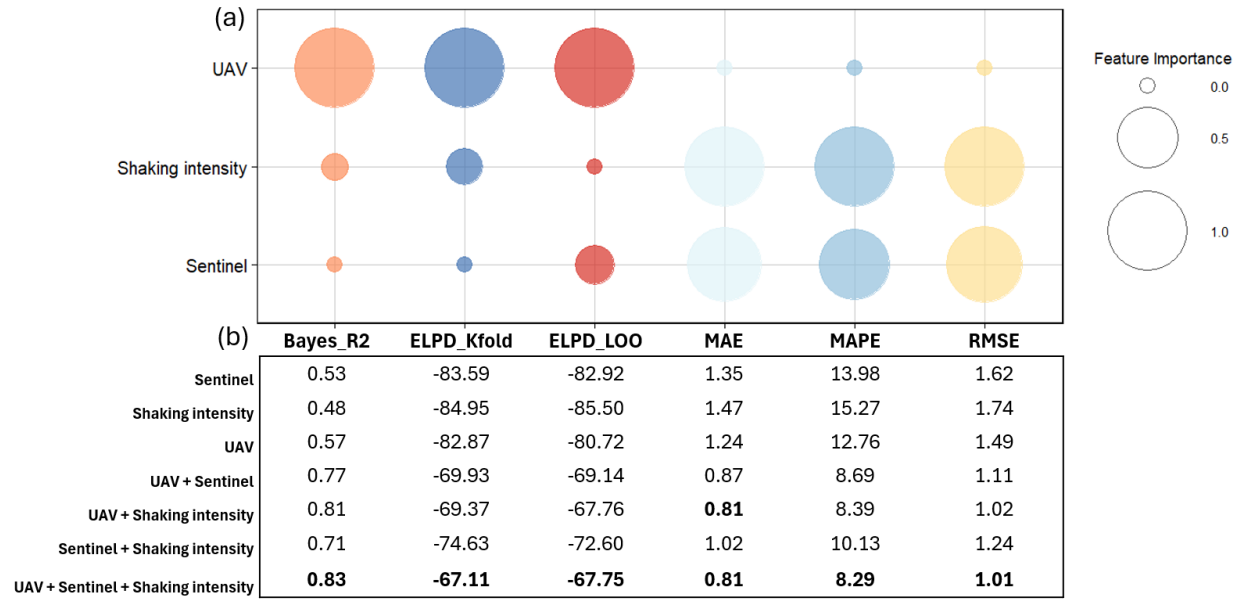


Fig. 7 Quantitative visualization of the relative influence of each variable within BHMs (a). The impact of each feature was evaluated across six performance metrics: RMSE, MAPE, MAE, ELPD-LOO, ELPD-KFold, and Bayesian R^2 . Each bubble represents the contribution of a given feature to a specific metric, with the size of the bubble scaled proportionally to its estimated relative importance. A legend is provided for scale interpretation, while panel 6b displays a summary table of metric values for each model configuration, offering a quantitative reference to complement the graphical analysis. Best-performing values for each metric are highlighted in bold.

As shown in Fig. 7a, UAV emerged as the most influential feature across all evaluation metrics. In particular, for error-related metrics (RMSE, MAE, MAPE), UAV contributed most significantly to error reduction, followed by Shaking intensity and, to a lesser extent, Sentinel. A similar pattern was observed for predictive quality metrics (ELPD-LOO, ELPD-KFold) and for the variance explained (Bayesian R^2), where UAV again shows the highest relative importance. The feature Shaking intensity showed an intermediate contribution: it ranked second for RMSE, MAE, and MAPE, while its impact on ELPD and Bayesian R^2 was

comparatively smaller. Sentinel consistently showed the lowest relative importance across all metrics, though it still provides a non-negligible contribution to model performance.

Fig. 7b reports the numerical performance metrics for models trained with individual features or combinations thereof. Models using a single feature yielded the lowest performance: Shaking intensity and Sentinel only models resulted in RMSE values of 1.74 and 1.62, respectively, with corresponding Bayesian R^2 values of 0.48 and 0.53. The model using only UAV showed slightly improved performance (Bayesian $R^2 = 0.57$; RMSE = 1.49) but remained inferior to BHMs with feature combinations.

Combining two features led to substantial performance gains. In particular, UAV + Shaking intensity and UAV + Sentinel outperformed the Sentinel + Shaking intensity model, especially in terms of Bayesian R^2 (0.81 and 0.77 vs. 0.71) and RMSE (1.02 and 1.11 vs. 1.24). The lowest MAE values were also achieved by UAV + Shaking intensity and UAV + Sentinel (0.81 and 0.87), highlighting the crucial role of UAV data in reducing absolute prediction error.

The model including all three features yielded the best results across all evaluated metrics, with a Bayesian R^2 of 0.83, and ELPD values of -67.11 (KFold) and -67.75 (LOO), indicating superior robustness under cross-validation. This model also achieved the lowest errors overall, with MAE = 0.81, MAPE = 8.29, and RMSE = 1.01.

These results highlight the added value of integrating data from multiple platforms. The qualitative analysis of relative importance confirmed that UAV-based high-resolution data represented the most influential single source of information for yield estimation. However, it was the simultaneous integration of all available sources that resulted in optimal model performance. While this approach increased the structural complexity of the model and entails higher computational cost for training and inference, it significantly improved both estimation accuracy and prediction consistency, particularly across observed and unobserved data.

Overall, these results support the use of spatially explicit data fusion strategies in agricultural modeling. Such approaches enhanced the complementarity between information sources and significantly boosted the predictive capabilities of BHM for yield estimation.

Model accuracy assessment and model validation

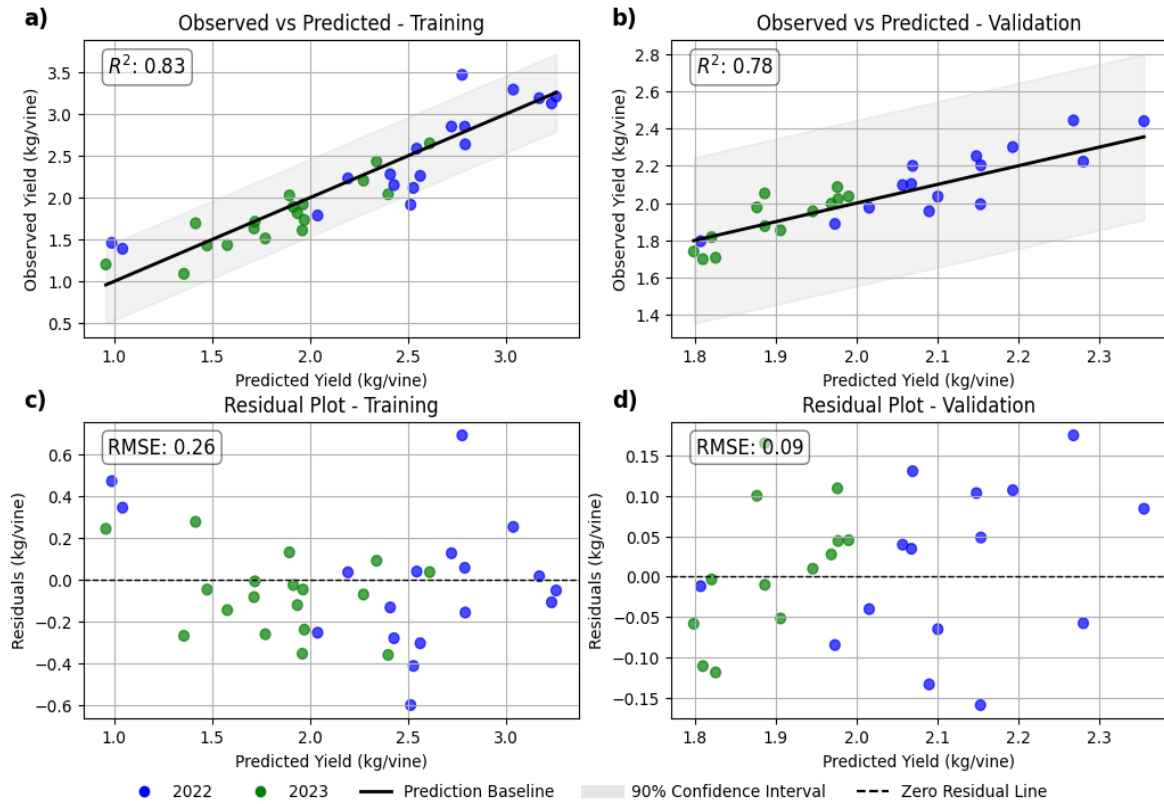


Fig. 8 Model performance evaluation for the BHM, shown separately for the training and validation datasets. Panels (a) and (b) display observed vs. predicted regression plots, where each point represents an actual observation (y-axis) plotted against the corresponding model prediction (x-axis). The black line indicates the fitted regression line, while the grey band represents the 90% confidence interval. Data points are color-coded by year: blue for 2022 and green for 2023. Panels (c) and (d) show the residual plots, where residuals (observed minus predicted values) are plotted as a function of the predicted values. The dashed line indicates the zero-error line, representing perfect prediction. Each panel is annotated with the corresponding R^2 (for a and b) and RMSE (for c and d) values.

In the training dataset (Fig. 8a), the model exhibited strong predictive performance, with a coefficient of determination $R^2 = 0.83$. The data points were closely aligned along the regression line, and the confidence interval remains relatively narrow, indicating good agreement between observed and predicted values. Both 2022 (blue) and 2023 (green) data followed the same general trend, with no notable year-dependent divergence. In the validation dataset (Fig. 8b), the model maintained satisfactory performance, with an $R^2 = 0.78$. Although data points showed increased dispersion compared to the training set, the regression line still followed a clear

positive trend consistent with the observed values. All observations fell within the 90% confidence interval, reinforcing the reliability of the model under independent testing conditions. Residual plots complement the performance assessment. In the training set (Fig. 8c), residuals were symmetrically distributed around the zero-error line, with a RMSE of 0.26. No systematic patterns were evident, suggesting the absence of model bias. A few extreme values were slightly over- or underestimated, but the overall spread remained contained. In the validation set (Fig. 8d), residuals showed an even tighter distribution around zero, with a notably lower RMSE of 0.09, outperforming the training set. This confirmed the observed trend of error reduction when aggregating data, likely due to the attenuation of noise commonly associated with this type of dataset. The absence of structured patterns in the residuals and the strong concentration of points around the zero-error line indicated that the model generalizes well, maintaining very low absolute error even on independent data.

Yield distribution and its spatial variability analysis

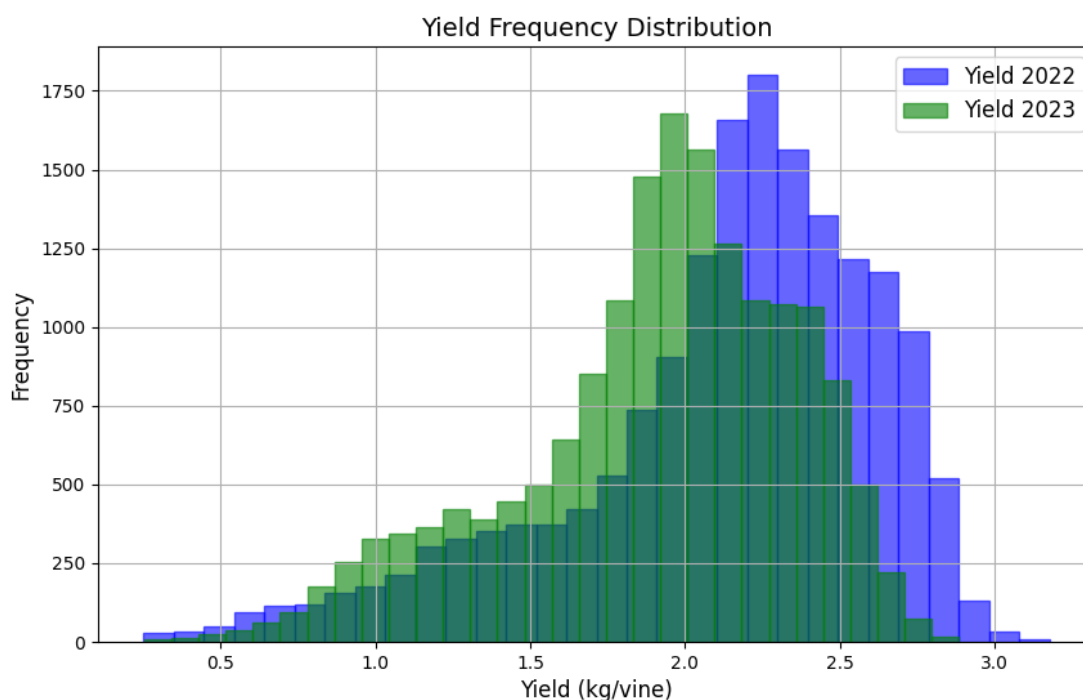


Fig. 9 Frequency distribution of yield (expressed in kg per vine) for two consecutive growing seasons, 2022 and 2023. The histograms are depicted in blue for 2022 and green for 2023. The x-axis represents yield in kg/vine, while the y-axis reports the absolute frequency of observations within each yield class.

The yield distributions represented in Fig. 9 reveal marked differences between the two seasons, while preserving consistent proportional trends. In 2022, yield values were generally higher, as confirmed by the frequency distribution, which peaked around 2.3–2.4 kg/vine and exhibited a longer tail toward higher yield values. In contrast, the 2023 distribution was shifted to the leftward, with most observations falling between 1.5 and 2.1 kg/vine and a peak near 2.0 kg/vine. Furthermore, the 2023 distribution appeared more symmetric and sharply peaked around its mode, indicating a lower dispersion compared to the broader and more skewed distribution observed in 2022. Overall, the comparison indicated both a decline in average yield and a reduction in variability in 2023 relative to 2022.

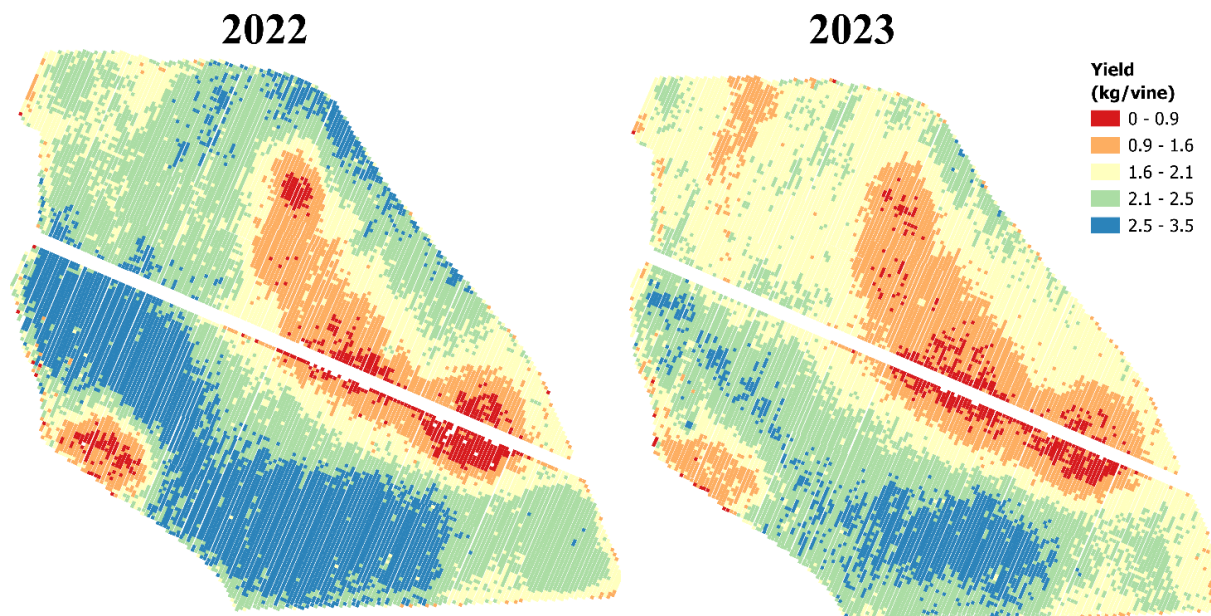


Fig. 10 Spatial distribution of yield (kg/vine) for the 2022 season (left) and 2023 season (right). Each block represents a georeferenced observation unit classified into five yield classes, color-coded from red (lowest yields) to blue (highest yields) as shown in the legend. The maps enable a visual evaluation of intra-parcel variability and changes in productivity between the two years.

The spatial representation of yield shows pronounced heterogeneity within the vineyard and reveals significant interannual differences (Fig. 10). In 2022 (left map), the highest-yielding zones (2.5–3.5 kg/vine, blue) were concentrated mainly in the southern and southwestern portions of the field. Medium-yield areas (2.1–2.5 kg/vine, in light green) were widespread, while very low-yield zones (<1.6 kg/vine, in red and orange) were more localized and sparse. In contrast, the 2023 map (right map), a substantial reduction in the extent of high-yield zones was observed, alongside a clear expansion of low-yields (red and orange), especially in the

central and northern regions. The intermediate yield class 1.6–2.1 kg/vine became dominant, reflecting a marked shift in productivity compared to the previous year.

This comparison revealed an overall reduction in productivity in 2023 and a more homogeneous spatial pattern toward lower yields. Notably, areas with high yield in 2022 transitioned to lower yield classes in 2023, suggesting a systematic and spatially consistent decline in performance. These spatial patterns corroborate the trends observed from the frequency distributions and predictive model outputs, confirming that 2023 experienced a decrease in yield.

Uncertainty distribution and its spatial variability analysis

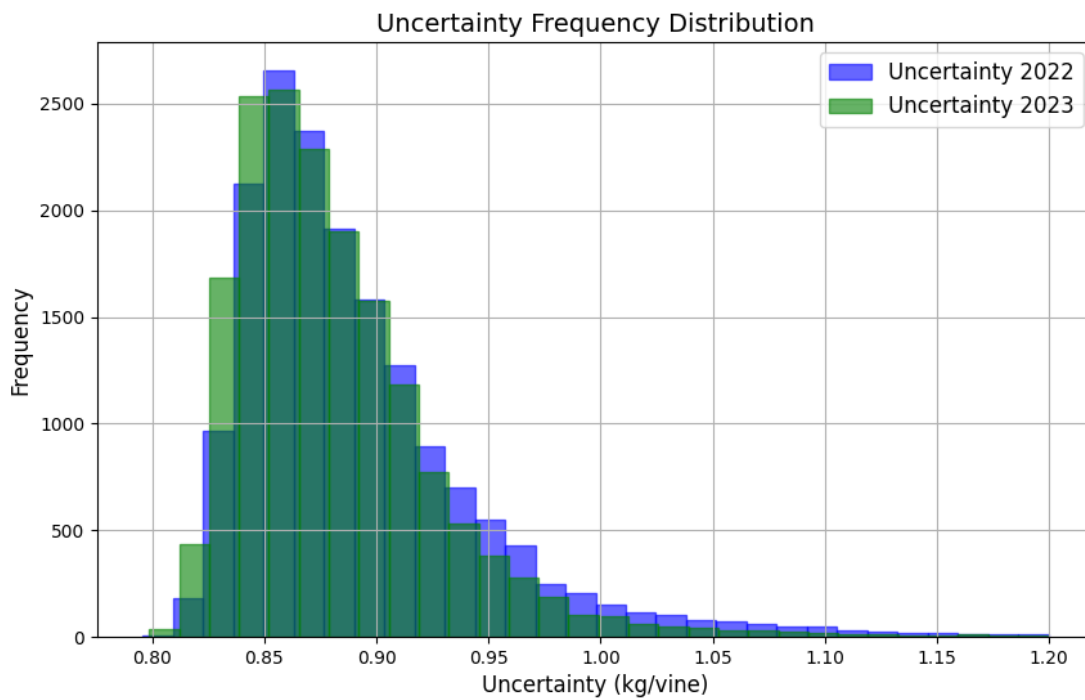


Fig. 11 Frequency distribution of the predictive uncertainty associated with the estimated yield (in kg/vine) for the 2022 (blue) and 2023 (green) growing seasons. The histograms display the frequency of uncertainty values computed for each georeferenced observation in the vineyard, based on the 5th and 95th percentiles extracted from the posterior predictive distribution (28,000 posterior samples per unit). The x-axis shows the magnitude of uncertainty per vine, while the y-axis represents the number of observations within each uncertainty class.

The uncertainty distributions were mainly similar across years, with most values concentrated between 0.84 and 0.90 kg/vine (Fig. 11). The 2022 distribution (blue) showed a slightly more pronounced peak around 0.86 kg/vine, while the 2023 histogram (green) had a comparable mode but with a smoother profile. Both years exhibited a right-skewed distribution, with tails extending up to approximately 1.20 kg/vine. However, the 2022 tail was slightly more extended, suggesting a higher presence of observations with elevated uncertainty compared to 2023. Overall, predictive uncertainties were comparable between years, though with a tendency toward more concentrated and less extreme values in 2023.

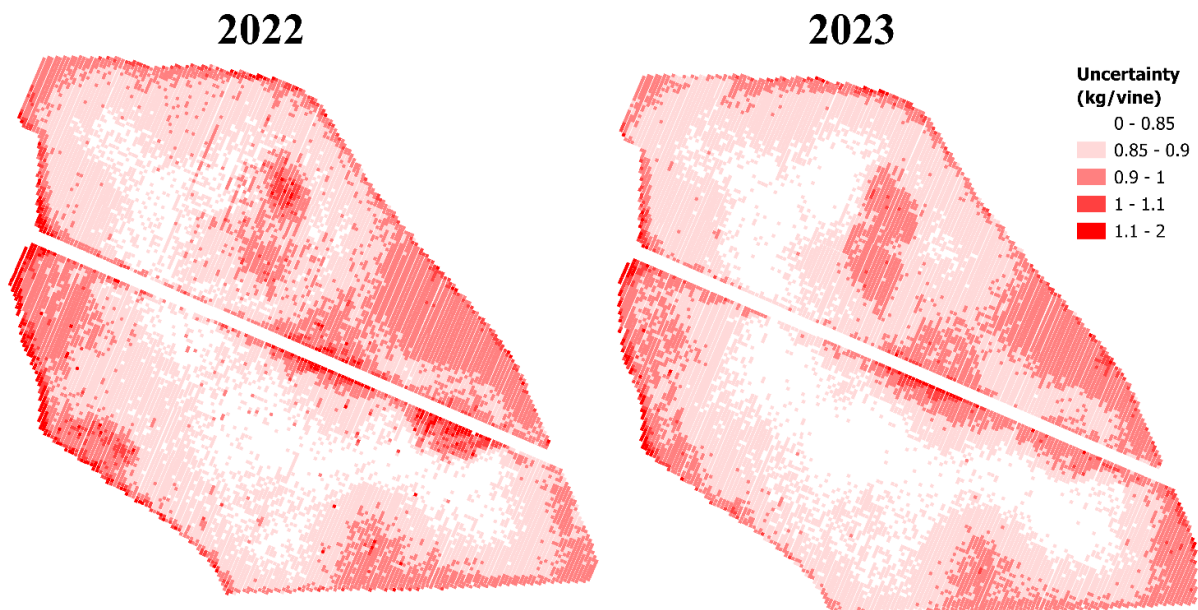


Fig. 12 Spatial distribution of predictive uncertainty (kg/vine) for 2022 (left) and 2023 (right). Each block corresponds to a georeferenced observation unit, classified into five uncertainty classes ranging from <0.85 kg/vine (white) to >2.0 kg/vine (red). These maps allow for detailed intra-parcel analysis of uncertainty and provide a visual comparison of its spatial intensity across seasons.

Fig. 12 illustrates the spatial pattern of posterior uncertainty associated with yield estimates for 2022 and 2023 seasons, as derived from BHM model. The maps showed heterogeneous pattern for estimation uncertainty across vineyard, with notable interannual differences in both extent and spatial localization. In 2022 (left map), estimation uncertainty appeared higher and more widespread. High uncertainty zones, characterized by values exceeding 1.0 kg/vine in (dark red), concentrated along the northeastern and southwestern edges of the field. The intermediate uncertainty class (0.9–1.0 kg/vine, in red) also covered large central portions of the vineyard, indicating areas where model predictions remained relatively less constrained. This spatial

configuration reflected greater local variability in vine performance or the presence of weaker signal-to-noise relationships between yield and covariates in these zones.

In contrast, the 2023 map (right map) exhibited a notable reduction in high-uncertainty zones. Central and eastern portions of the field displayed a higher concentration of low-uncertainty values (<0.85 kg/vine, in light red), indicating greater confidence in the model's yield predictions. Higher uncertainty classes appeared more fragmented and were confined mainly to the edge regions, suggesting a clearer and more stable estimation process across most of the vineyard surface. The central area, corresponding to zones with medium-to-low yield classes, showed more constrained uncertainty in 2023 compared to 2022, suggesting improved model resolution in those regions.

Discussions

Model development, sensitivity analysis across alternative construction scenarios and model validation

The methodological framework developed in this study allowed the construction of an accurate and reliable yield mapping model robust enough to perform effectively under real field conditions. The validated model facilitated spatial yield inference and analysis of spatial variability, including quantification of prediction uncertainty. Thus, it provides a user-friendly, robust tool for practical yield mapping applications in real agricultural settings.

Several training scenarios were simulated, leading to the selection of a hierarchical partially pooled Bayesian model, trained using Sampling Unit A and incorporating geospatial characteristics. This model demonstrated high precision and accuracy, showing notably low prediction errors. When evaluated on the validation dataset, the model maintained a substantial portion of its accuracy, with errors even further reduced in aggregated data predictions. This error reduction indicates minimal model bias, demonstrating the suitability of the Bayesian hierarchical framework adopted.

When assessing model sensitivity to different strategies of incorporating annual variability, three pooling approaches were examined: total pooling, no pooling, and partial pooling. Results clearly indicated superior performance of the partially pooled approach over the other two methods, with particularly significant advantages compared to no pooling.

Although a direct comparison with other studies on the same topic is not possible due to the absence of similar Bayesian implementations on vineyard in literature, multiple lines of evidence from different application contexts support the superiority of partial pooling. For instance, Van Boekel (2021) showed that partial pooling delivered the best predictive capacity and reduced parameter variance in microbial kinetics experiments. Likewise, Niu et al., (2024) observed higher inference precision from partially pooled models compared to complete or no pooling in a geochemical study analyzing metal grade relationships. Similarly, Feng et al. (2024) demonstrated that sharing information between adjacent overcoming tests via partial pooling strategies effectively reduced uncertainty. Salakpi et al (2022) also reported improved accuracy and precision in agricultural drought forecasting across spatially diverse regions. Indeed, the partially pooled approach effectively captured random effects associated with year-to-year variability, reflecting real-world conditions where relationships between NDVI and yield remain consistent but vary in magnitude and intercept annually. Annual meteorological conditions influence canopy growth, thereby modulating crop responses despite stable genotype and site-specific environmental conditions. Interannual variations in temperature, rainfall, and radiation regimes can significantly affect grapevine productivity, introducing variability in yield outcomes and associated spatial patterns across growing seasons (Bramley and Hamilton, 2004; Fuente et al., 2015). These dynamic interactions underscore the importance of accounting for temporal variability when interpreting yield trends and evaluating model performance. In this context, the comparison between partially pooled and total pooled modeling approaches reveals differences in how temporal dynamics are captured. Although both strategies produce consistent results, the partially pooled model tends to better accommodate interannual variations in yield responses (Rising and Devineni, 2020). Nonetheless, the observed differences between pooling strategies remain modest, suggesting a relatively stable temporal structure in yield outcomes under the prevailing environmental variability.

Spatial resolution during model training significantly influenced predictive performance. Models trained with Sampling Unit A demonstrated better performance than those using Sampling Unit B, primarily through reduced prediction errors (Fig. 6). This improvement likely arises from sampling methodology and inherent data characteristics. Yield sampling per individual plant, typical in vineyard studies, often introduces measurement inconsistencies because RS data are collected at surface-area units rather than individual plant levels. In vineyards, plant canopies typically form continuous structures, with shoots intertwining across adjacent plants. Hence, yield attributed to a specific plant can spatially overlap with adjacent

plants. Plant-level growth, vigor, and yield exhibit clear spatial patterns, but also notable intra-plant variability due to complex competition dynamics for resources such as light and nutrients (Reynolds et al., 2004). Consequently, RS observations at finer spatial resolutions (e.g., 2 meters) that aggregate yield from two plants can be excessively noisy and thus suboptimal for model training (Victorino et al., 2022a). Conversely, training models using aggregated data at a larger spatial scale (e.g., 6 linear meters encompassing multiple plants) substantially reduced prediction errors, yielding more stable and accurate models. A promising alternative might involve yield sampling per linear meter of vegetation rather than individual plants, particularly suitable for crops grown in continuous canopy systems (Victorino et al., 2022b). This approach could significantly enhance the robustness and predictive capacity of yield estimation models.

The incorporation of spatial coordinates as an informative layer within model construction proved advantageous. Models incorporating x and y coordinates demonstrated markedly improved predictive metrics and increased reliability in future predictions. This result underscores the importance of explicitly modeling spatial autocorrelation, given that adjacent points typically exhibit higher similarity in yield characteristics compared to more distant locations. This principle is well established in the frequentist framework, particularly through Universal Kriging, where spatial dependence is modeled using variogram-based covariance structures (Cressie., 1993). However, adopting a Bayesian perspective offers several additional advantages for spatial mapping. Bayesian spatial models provide a coherent probabilistic formulation in which uncertainty is propagated across all levels of the model, enable flexible specification of covariance structures, and naturally accommodate spatially varying effects and non-stationarity (Finley et al., 2011; Finley and Banerjee, 2020). Similar conclusions were drawn by Cao et al. (2022), they used spatially correlated random parameters in a Bayesian framework to optimize nitrogen dosing, while Park et al., (2023) applied spatially varying coefficient models to capture regional differences in crop responses to weather. Niyibizi et al., (2021) further demonstrated that Bayesian kriging enhances prediction robustness by smoothing spatial trends in skewed yield data, confirming that accounting for spatial relationships thus substantially reduces prediction noise and enhances accuracy.

Additionally, simulations conducted in this study systematically evaluated combinations of predictive features: UAV-derived NDVI, Sentinel satellite data, and the grape harvester's shaker intensity per unit length. Overall, predictive performance improved incrementally with the inclusion of more features, showing a substantial performance increase when moving from a

single feature to two features, and a moderate yet significant improvement from two to three features. Fig. 5a qualitatively highlights the relative importance of each feature: UAV data significantly boosted predictive accuracy due to their high spatial resolution, followed by Shaking intensity, while Sentinel data provided the smallest incremental benefit among the features tested, though still contributing meaningfully to overall model accuracy. Consistently with the finding in the related literature, the combination of high-resolution UAV data and Sentinel-derived data is particularly advantageous; UAV data, although extremely detailed, can sometimes introduce considerable noise, while Sentinel data, highly correlated but less granular, effectively correct and stabilize predictions (Barriguinha et al., 2021; Laurent et al., 2021). The Shaking intensity feature, reflecting harvester operational shaker intensity as a proxy for crop density and productivity, significantly improved model training, confirming its correlation with crop yield conditions during mechanical harvesting operations, confirming the observation of Gras et al., (2024) on vineyard and by Momin et al., (2019) in sugarcane.

The model exhibited strong predictive capability and generalization across both training and validation phases. During training, the high coefficient of determination ($R^2 = 0.83$) and the narrow confidence interval reflected robust internal consistency and temporal stability, with no interannual divergence between 2022 and 2023 observations. In validation, the model retained a high level of accuracy ($R^2 = 0.78$), with predictions remaining within the 90% confidence interval and aligned with the overall regression trend, thereby confirming its reliability under independent testing conditions. Interestingly, although the validation set exhibited a marginally lower R^2 , the prediction error measured by RMSE decreased from 0.26 in the training phase to 0.09 in validation. This result, though apparently counterintuitive, can be attributed to the effects of spatial data aggregation, which tend to attenuate high-frequency measurement noise and reduce local variability. Moreover, the validation subset may have exhibited increased internal homogeneity, further contributing to reduced error dispersion. These dynamics are consistent with previous findings in remote sensing-based agronomic modelling, where spatial averaging often improves predictive stability (Khechba et al., 2025). This phenomenon occurs because validation data, aggregated by harvester load, represent combined areas of varying productivity levels (low, medium, high), narrowing the range of yield variability compared to the training dataset. Specifically, while observed yield values in the training set ranged broadly from approximately 1.0 to 3.5 kg per vine, the validation dataset exhibited a narrower range, from approximately 1.6 to 2.5 kg per vine. Under such conditions, indices like R^2 , which measure explained variance, naturally decrease due to reduced yield variability. However, the

decreased variability also leads to smaller prediction errors, as observed in Fig. 6a, where model predictions deviated most significantly from observed values at extreme yield levels, absent in the validation set. Thus, aggregated yield conditions enhance model robustness and reduce prediction error, demonstrating its suitability and reliability for practical field-level yield prediction applications. Overall, the limited decline in R^2 , the symmetry and lack of bias in residuals, and the reduction in RMSE collectively indicate that the model does not suffer from overfitting and performs reliably across datasets within the adopted spatial structure.

Yield distribution and its spatial variability analysis

The constructed model enabled the generation of high-resolution yield maps for the 2022 and 2023 growing seasons, allowing for a detailed analysis of spatial and temporal variability in vineyard productivity across years. Overall, results indicate an approximate 15% reduction in yield between 2022 and 2023, while spatial yield patterns within the field remained largely stable. The comparative analysis between the two growing seasons highlights the significant influence of meteorological conditions on vineyard productivity. In particular, the 2022 season was characterized by near-normal climatic conditions, with a regular distribution of rainfall and slightly above-average temperatures, especially during the summer months. These conditions, typical of Mediterranean viticultural environments, favoured grapevine vegetative and reproductive development, especially during the early phenological stages such as budburst and inflorescence initiation. As noted by Keller et al., (2010), moderately warm temperatures during spring can enhance yield potential by increasing leaf area, flower size, and fruit set. In contrast, the 2023 season exhibited a markedly irregular climatic pattern. Exceptionally high rainfall was recorded in May (120 mm), followed by an extended drought and a series of heatwaves during the berry growth and ripening phases. This sequence of weather extremes created a highly unfavourable environment for grapevine development. Rainfall during the pre-flowering and fruit set stages, combined with below-average temperatures and reduced solar radiation, may have adversely affected flower fertilization and differentiation, ultimately compromising yield formation. According to Lebon et al., (2008), both cool ($<15^{\circ}\text{C}$) and excessively warm ($>35^{\circ}\text{C}$) temperatures can negatively impact fruit set, while low light conditions may induce carbon deficits in inflorescences due to their low sink priority relative to other vine organs. The combined effects of water scarcity and extreme summer heat further exacerbated the situation in 2023. As observed by Van Leeuwen et al., (2019), the increasing frequency of extreme

weather events, such as heatwaves, is making water stress an increasingly critical constraint for Mediterranean viticulture. Water deficit during the key phenological phases of berry development and ripening has been identified as a major limiting factor for vineyard productivity (Chacón-Vozmediano et al., 2020). Grapevines typically respond to drought conditions by reducing leaf area and limiting cluster number as a strategy to minimize transpiration and optimize water uptake (Keller et al., 2016). However, these adaptive mechanisms also reduce the photosynthetically active surface, directly affecting berry size and overall yield (Ojeda et al., 2002). Moreover, since grape yield is closely linked to the photosynthetic activity of the canopy and, consequently, to the amount of light intercepted by the leaves (Kliewer and Dokoozlian, 2005), the reduced radiation and thermal stress observed in 2023 likely impaired leaf physiological function and photosynthetic efficiency. Altogether, these findings suggest that the yield reduction observed in 2023 resulted from the synergistic action of multiple abiotic stressors, such as drought and heat stress, negatively impacting both physiological and reproductive processes in the grapevine.

In 2023, the combination of spring rainfall and elevated summer temperatures not only affected grapevine physiology directly but also promoted the onset of fungal diseases. Heavy precipitation during flowering and fruit set created favourable conditions for the spread of *Plasmopara viticola* (downy mildew) and *Erysiphe necator* (powdery mildew), both of which are known to reduce yield and fruit quality (Gessler et al., 2011). In particular, leaf damage induced by these pathogens may have limited photosynthetic activity and carbohydrate accumulation, thereby affecting both current-season productivity and vine vigor in subsequent seasons (Jermini et al., 2010).

These stressors likely contributed to the yield decline observed in 2023 (8.5 t ha^{-1}), compared to 2022 (9.6 t ha^{-1}), reinforcing the need to account for weather-induced biotic pressures in predictive yield models. Soil properties significantly influenced grapevine vigor and yield, particularly under the contrasting climatic conditions of 2022 and 2023. The stable spatial patterns of vegetative growth observed across seasons reflect underlying pedological variability. As shown by Bramley and Hamilton, (2004), soil depth is a key driver of yield variability, with deeper soils supporting greater yield. Soil depth and clay content affect root development, water retention, and aeration (Bodin and Morlat, 2006), while excessive clay can restrict root penetration and reduce oxygen availability (Tardáguila et al., 2011), increasing plant sensitivity to drought. In the present study, yield reductions observed in 2023 appeared to

be spatially associated with areas of consistently lower vegetative vigor. These results are further supported by previous research conducted in the same vineyard (Catania et al., 2025), which demonstrated a significant spatial association between vine vigour and the physico-chemical properties of the soil through monitoring. Specifically, high-vigor levels corresponded to zones with raised soil organic carbon (SOC) and total nitrogen, whereas low-vigor areas were associated with higher soil bulk density and increased soil penetration resistance, which are known to restrict root development and reduce water availability. This pattern suggests that site-specific soil conditions, potentially influencing water availability and root system efficiency, may have increased vine susceptibility to drought and heat stress during berry development. As noted by Echeverría et al., (2017), the amount of water available in the root zone plays a critical role in modulating vine growth, disease incidence, and fruit quality, particularly under dry conditions. Moreover, the interannual variability in yield response underlines the importance of understanding the interaction between soil and climate conditions (Canicatti et al., 2025b). As reported by Anastasiou et al., (2023), the effect of soil properties on grape yield and quality is season-dependent, being strongly modulated by precipitation and temperature dynamics.

Altogether, these observations support the hypothesis that intra-vineyard variability in growth and yield is the result of complex interactions between pedological features and climatic variability, further reinforcing the need for site-specific soil characterization and targeted management strategies in precision viticulture (Bramley and Hamilton, 2004; Fuente et al., 2015).

Uncertainty distribution and its spatial variability analysis

The approach adopted in this study enabled the estimation of grapevine yield accompanied by a credible interval and allowed these predictions to be mapped to assess uncertainty and its spatiotemporal variability. Overall, the distribution of uncertainty showed a remarkably similar pattern across the two years, with values typically ranging between 0.84 and 0.90 kg/vine. These uncertainty values were generally lower in the central portion of the vineyard, indicating more precise predictions, whereas uncertainty tended to increase toward the field boundaries.

This spatial pattern may be explained by the behavior of the shaking intensity variable, derived from harvester tracking. In central vineyard zones, shaking intensity aligned more closely with the patterns observed in NDVI-based predictors, contributing meaningfully to the yield

estimation. However, at the beginning and end of rows, areas characterized by natural deceleration and acceleration during turning manoeuvres, the shaking intensity signal became less informative, deviating from the other predictors. While this misalignment had limited impact on predicted yield, it led to a notable increase in the uncertainty associated with those predictions. Similar findings were reported by Ma et al., (2021) in a Bayesian yield prediction study for maize, where uncertainty increased in regions with less informative or more heterogeneous inputs, highlighting a clear relationship between data quality and the width of predictive intervals. Beyond this main trend, other high-uncertainty zones were also observed. For instance, the north-central part of the vineyard displayed elevated uncertainty despite relatively uniform shaking intensity values. In these areas, both UAV and Sentinel NDVI suggested low vegetative vigor, while the shaking intensity layer remained stable, likely due to operator misjudgement during harvesting. This discrepancy between predictors further emphasizes the utility of uncertainty quantification: when secondary predictors diverge from the trends established by primary ones, their influence may not directly bias the prediction but rather amplify predictive uncertainty. The levels of uncertainty observed in this study were generally acceptable, corresponding to approximately $\pm 20\%$ of the population mean. Nonetheless, given the limited size of the dataset and the specific environmental and varietal conditions evaluated, the authors recognize that the robustness of the model could be significantly enhanced by expanding the dataset to other cultivars and environments. Moreover, the definition of prior distributions represents an additional avenue for improvement. Although weakly informative priors were employed in this study, due to limited prior knowledge and the absence of specific references in the literature, it is well established that more tailored and informative priors can help reduce predictive uncertainty. For example, Bazrafshan et al. (2022) demonstrated that well-informed priors, derived from expert knowledge or previous experiments, substantially improved inference accuracy and precision. Therefore, future work should explore the implementation of customized prior specifications, grounded in prior empirical evidence or expert elicitation, to further narrow the uncertainty bounds associated with yield predictions in viticulture.

Limitations and perspectives

The framework presented in this study demonstrated good capabilities for yield mapping and quantification of associated uncertainty. Nevertheless, some limitations persist, alongside numerous avenues for future development.

Among the principal limitations, one is the absence of comparable Bayesian applications for yield estimation in viticulture, which limits direct benchmarking and comparative evaluation. Nonetheless, successful Bayesian implementations in other cropping systems, mainly herbaceous, demonstrate the adaptability of Bayesian frameworks to complex, multi-source agricultural data (Abbaszadeh et al., 2022; Lu et al., 2025; Ma et al., 2021; Roth et al., 2024; Wu et al., 2022). These studies highlight the capacity of Bayesian models to capture spatial heterogeneity, integrate RS with process-based models, and provide uncertainty-aware predictions. Within this context, the present work represents a novel contribution to viticulture, offering not only a functional yield mapping framework but also a foundation for broader applications. Its structure and methodological flexibility suggest potential for extension to other perennial cropping systems, where spatial complexity and long-term management dynamics similarly benefit from probabilistic and data-integrative modeling approaches (Song et al., 2024).

In this work, the uncertainty associated with predictions, although generally acceptable, remains elevated in specific areas of the vineyard, particularly near plot boundaries and in zones where predictors are misaligned (Fig. 12). The spatial representation of predictive uncertainty enables refined intra-parcel risk assessment and supports the implementation of smart scouting strategies; whereby field inspections are selectively directed to high-uncertainty zones to validate or refine model outputs. In contrast, low-uncertainty areas can serve as reliable references for operational decisions. Additionally, the model tends to show reduced accuracy in extreme yield values, such as very low or very high yields (Fig. 8). It is also important to emphasize that the current framework predicts only one yield component, the number of grapes, implying a partial estimation of overall yield. Future improvements should explore the integration of additional yield components, the use of temporally continuous predictor variables, and the implementation of uncertainty-aware decision support tools capable of dynamically adapting vineyard management strategies based on both predicted outcomes and their associated confidence levels. For example, the predictive performance of Sentinel-based covariates is strongly influenced by the timing of image acquisition. Consequently, further

studies that explicitly incorporate the temporal dimension of Sentinel data could provide deeper insights into the relationship and improve predictive accuracy.

Further limitations involve operational aspects. For instance, the harvester shaker intensity parameter, employed as a proxy for vine density, can be prone to human errors, leading to misalignment with other predictors, especially during acceleration and braking phases (Fargnoli et al., 2018). Moreover, the model assumes a causal relationship between yield and speed (interpreted as a proxy for the beating frequency per linear meter), which may not hold true for all machines. In fact, in more advanced systems, the shaking frequency is dynamically adjusted based on the forward speed to maintain a constant number of impacts per unit area. Finally, in the most sophisticated systems, sensors can automatically regulate these parameters, enhancing the operational efficiency of the machines (Paraforos et al., 2019). Additionally, building the spatial grid and managing UAV-derived data entail substantial computational effort, potentially limiting widespread adoption, especially among larger-scale wineries or viticultural operations.

Despite these limitations, considerable opportunities for improvement exist. Although this study serves primarily as a proof of concept, demonstrating the feasibility of integrating multisource remote sensing and harvester tracking data within a Bayesian hierarchical framework, the approach is inherently flexible and scalable. The current framework, even without further implementation, can be directly tested and validated in different agronomic contexts, encompassing various grape varieties and diverse climatic conditions. Nonetheless, given the Bayesian hierarchical structure implemented in brms, future studies could explicitly incorporate multiple hierarchical grouping factors, such as cultivar-specific, site-specific, or regional-level effects, enabling partial pooling across different growing contexts and thus refining prediction accuracy and reduce uncertainty (Bohman et al., 2023). Expanding the dataset to include additional grape varieties and diverse agronomic environments could enhance the model's generalizability and robustness. Grape variety can significantly influence model performance because of inherent differences in vigor and vegetation-yield relationships, directly affecting input predictors such as NDVI. Therefore, explicitly modeling cultivar effects could refine prediction accuracy considerably. Integrating supplementary predictive variables, such as soil characteristics or temporal dynamics of vegetation indices, could further refine prediction accuracy (Andrade et al., 2023; Sirsat et al., 2019). Additionally, extending the temporal scope by incorporating data from multiple growing seasons would allow for dynamic modeling techniques that explicitly account for climate-driven yield variability. A particularly

promising extension involves combining the current Bayesian framework with phenological models that characterize seasonal berry growth patterns. Such an integration would permit direct estimation of average cluster weight and, consequently, enable more accurate predictions of total yield at the vineyard scale (Ellis et al., 2020).

Furthermore, integrating computer vision algorithms, extensively explored in literature for single-plant yield estimation using field-acquired imagery, represents a promising extension of this Bayesian framework. In such scenarios, the proposed model could spatially upscale local estimates derived from artificial vision techniques, producing continuous, georeferenced yield maps (Herrero-Huerta et al., 2015; Zheng et al., 2024). Another fundamental aspect is the refinement of priors: employing more informative priors, based on previous knowledge or well-established literature, could significantly reduce estimation uncertainty (Habibi et al., 2025). Future developments might benefit from increasing the specificity of these priors.

Additional opportunities include exploring novel sampling techniques, such as linear-meter vegetation sampling, which may better reflect the continuous structure of vineyard canopies (Victorino et al., 2022a). The use of low-cost drones and GPS technologies could also facilitate broader adoption of the methodology. Finally, the model offers substantial practical applications, such as generating high-resolution post-harvest fertilization maps and supporting the implementation of site-specific approach towards advanced precision viticulture. Beyond these applications, the spatial identification of yield-limiting zones enables more informed decision-making, including the prioritization of selective harvesting operations (Bramley et al., 2011). Additional strengths of the proposed framework include early plot-scale yield estimation, which supports more efficient harvest planning and ensures timely post-harvest logistics. This preserves grape quality and reduces the risk of pre-fermentation or must losses caused by prolonged field exposure. As noted by Catania et al., (2009), controlling the time interval between harvest and transfer to the cellar is essential for preserving wine quality, and early yield information can play a decisive role in achieving this objective. Moreover, integrating predictive yield maps into vineyard information systems can support resource optimization and strategic planning, thereby improving sustainability and growers' ability to adapt to spatial and temporal variability within the vineyard. These applications are consistent with the principles of site-specific management in viticulture, where spatialized data guide interventions to optimize production efficiency and environmental sustainability.

Conclusions

The hierarchical Bayesian partially pooled approach demonstrates considerable potential for improving vineyard yield mapping. Compared to traditional methods, this approach enables better integration of different and complementary data sources, maximizing the value and utility of the available information.

The simulation results demonstrated that partial pooling strategy and the inclusion of spatial dependence positively affected model performance, improving model robustness and predictive capability. The selected BHM exhibited high predictive accuracy, validated through comparison with ground truth data. Incorporating data from multiple sources substantially improved the robustness and accuracy of the analysis by capturing a broader range of information, improving accuracy and reducing potential biases. The developed model was utilized to map yield across two growing seasons, revealing a 15% reduction between the seasons and allowing for identification of uncertainty.

The BHM model demonstrated strong generalization capabilities, presenting a promising framework; incorporating additional data across multiple growing seasons, different fields, and various grape cultivars could further enhance its robustness and predictive accuracy, which was somewhat constrained in this study due to the limited data range. Furthermore, the Bayesian framework inherently provides not only yield prediction maps, but also quantifiable measures of uncertainty associated with each estimate, significantly enhancing decision-making confidence.

Future research directions include integrating this methodology with phenological models of berry development stages. Such integration has the potential to substantially improve agronomic management practices and operational decision-making processes. Ultimately, the aim is to develop a globally applicable, robust yield forecasting model that effectively utilizes geospatial technologies combined with advanced Bayesian methods.

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Ground truth sampling methods affect accuracy of UAV-based vineyard yield estimation: a case study

Abstract

Purpose: Accurate ground-truth data are essential for training reliable remote sensing (RS) models for vineyard yield estimation. However, previous UAV-based studies have mainly relied on single-vine sampling, which can introduce geometric inconsistencies due to canopy overlaps, vine spacing, and pruning configuration in Vertical Shoot Positioning (VSP) systems. This study aimed to assess how the choice of ground-truth sampling method, plant-based versus linear canopy-segment-based, affects the accuracy and robustness of UAV-derived yield models.

Methods: UAV multispectral imagery was acquired at two phenological stages, BBCH 73 and BBCH 85, over a commercial vineyard trained to a VSP system. Yield data were collected using two ground-truth approaches, a plant-based method, recording the grape fresh weight per vine, and a meter-based method, measuring yield along contiguous one-meter canopy segments. UAV

images were processed to derive spectral (NDVI) and geometric (fraction canopy cover, F_c) variables. Three estimation frameworks were evaluated: (i) linear regression models; (ii) machine learning (ML) algorithms (Efficient Linear, Support Vector Machine, Random Forest, and Gaussian Process Regression); and (iii) a Bayesian inference model.

Results: Across all frameworks, the linear-based sampling approach outperformed the plant-based one. Linear regressions yielded higher determination coefficients ($R^2=0.78$) and lower RMSE. ML algorithms achieved R^2 between 0.70–0.76 for linear sampling versus 0.15–0.27 for plant sampling. Bayesian model trained on linear sampled data demonstrated the highest predictive accuracy, achieving an R^2 of 0.84 with an RMSE of $0.26 \text{ kg} \cdot \text{m}^{-1}$ and a mean absolute error of $0.22 \text{ kg} \cdot \text{m}^{-1}$. In contrast, the model trained on vine-level data exhibited markedly lower performance ($R^2 = 0.41$, $\text{RMSE} = 0.55 \text{ kg} \cdot \text{vine}^{-1}$). At the field scale, the linear-based sampling strategy, when coupled with Bayesian inference, delivered high-fidelity yield estimates with reduced posterior uncertainty.

Conclusion: Ground-truth sampling design significantly affected UAV-based vineyard yield estimation. Sampling contiguous canopy segments preserves spatial continuity and mitigates geometric bias, enhancing model transferability and reliability across analytical frameworks. This approach provides a robust methodological foundation for scalable RS-based yield modelling in VSP vineyards.

Keywords: Remote sensing, bayesian inference, uncertainty quantification, precision viticulture, multispectral imagery.

Introduction

Grapes are one of the most widely grown fruit crops in the world, and environmental conditions, the physiological state of the plants and management practices can greatly influence grape yield and quality (Matese and Di Gennaro, 2015). In recent years, technological advances have introduced new tools to support this sector, giving rise to the concept of precision viticulture (PV). PV is based on the analysis, interpretation and management of spatial and temporal variability with the aim of optimising agronomic efficiency, improving economic and environmental sustainability (Ferro et al., 2023; Matese and Di Gennaro, 2015).

Recent advances in remote sensing (RS) techniques offer a valuable and efficient tool for monitoring vines at different scales. Among the various RS platforms, satellites and unmanned

aerial vehicles (UAVs) are currently widely used and offer clear advantages for plant growth and health assessment (Bollas et al., 2021; Di Gennaro et al., 2019a). While satellite-based imagery provides valuable insights at the field and regional scales, its spatial resolution can be insufficient to capture the plant-scale variability in small and/or fragmented fields (Khaliq et al., 2019; Matese et al., 2017). As a complementary technology, UAVs enable rapid acquisition of ultra-high-resolution data at low operational costs and offer great flexibility in terms of flight scheduling and sensor integration (Canicattì and Vallone, 2024; Mogili and Deepak, 2018). Multispectral cameras capture reflectance signatures across spectral regions, enabling the extraction of biophysical information using vegetation indices (VI). Normalised difference vegetation index (NDVI), in particular, is widely used as a proxy of vigour and health status evaluation of a wide range of crops, including vineyard (Bannari et al., 1995; Rouse et al., 1974; Xie et al., 2014). UAV-based multispectral imagery further enhanced vineyard canopies monitoring by enabling precise delineation of grapevine vegetation from background (i.e. weeds, soil and canopy's shadows) (Campos et al., 2014; Towers and Poblete-Echeverría, 2021). These tasks are increasingly supported by machine learning (ML) and deep learning (DL) algorithms for classification and segmentation of images (Cinat et al., 2019; Hossain and Chen, 2019; Pádua et al., 2022). Canopies detection allows the extraction of a spectral and geometrical features (Catania et al., 2023b; Comba et al., 2020; Di Gennaro and Matese, 2020). Geometric features include canopy area (CA), thickness, canopy volume and fraction cover (Fc) (Campos et al., 2021a). The latter feature represents the ratio between canopy area and the available space per vine, has gained relevance in vineyard management. It is increasingly employed to support agronomic decisions, guide irrigation strategies, and serve as a key input for crop simulation models (Berry et al., 2024; Gao et al., 2020; Roma et al., 2025). Accurate estimation of vineyard yield is a key requirement for efficient harvest planning, logistical organization, and grape quality forecasting. However, yield estimation remains a challenging process due to the strong spatial and temporal variability of vine canopies and the practical constraints associated with field data collection. These limitations restrict the number of sampling sites that can be monitored within a vineyard (Guilpart et al., 2014; Júnior et al., 2018).

Traditionally, yield has been determined through manual measurements of the number of clusters, berries per cluster and average berry weight, with results typically expressed per vine or per unit area (Araya-Alman et al., 2019; Fuente et al., 2015). However, these measurements are subject to counting errors, particularly under dense canopies, and are influenced by marked

intra- and inter-vine variability, as cluster weight may strongly differ even within the same plant (Clingeleffer and Krstic, 2003). From a statistical standpoint, an optimal sampling protocol should represent spatial distribution and variability in the vineyard population.

Since canopy architecture and physiological processes vary across space and time (Ferro et al., 2023), sampling strategies must be designed to capture this embedded heterogeneity. Over the years, vineyard sampling methodologies have evolved from random to spatially informed approaches that account for within-field variability. Designs such as the randomized complete block (RCBD) and spatially balanced complete block (SBCB) have been developed to ensure a more uniform distribution of sampling points and to reduce the influence of underlying spatial gradients (Acevedo-Opazo et al., 2010; Bramley and Hamilton, 2004; Schoedl et al., 2012). The concept of spatial balance has since been extended to integrate RS data, including VIs and canopy structural metrics. This integration has proven effective in optimizing sample size, reducing it by up to 69%, and in minimizing travel distance during field surveys by up to 90%, without compromising accuracy (Meyers et al., 2011; Meyers and Vanden Heuvel, 2014). More recently, the use of management zones defined by yield variability or VIs has emerged as an efficient and statistically robust approach in PV (Laurent et al., 2021; Squeri et al., 2021; Valente et al., 2024).

Parallel to these advances in sampling design, numerous studies have investigated the use of UAV-based RS for vineyard yield estimation. Ballesteros et al. (2020) achieved high prediction accuracy ($RMSE = 0.5 \text{ kg vine}^{-1}$; $RE = 12.1\%$) by combining vegetation indices and F_c metrics in a bilateral cordon system. Di Gennaro et al. (2019) obtained over 84% accuracy in yield prediction through automated cluster detection on RGB imagery, while Leolini et al. (2023) and López-García et al. (2022) reported $RMSE$ values ranging from 0.21 to $0.39 \text{ kg vine}^{-1}$ in vineyards with different pruning systems. Although these studies confirm the potential of UAV imagery for accurate yield estimation, their reliance on vine-based ground-truth data limits the generalization of models across diverse vineyard architectures. Expressing yield per linear meter of canopy (kg m^{-1}) rather than per vine provides a geometry-independent and spatially consistent reference, particularly suitable where canopy forms a continuous wall. This metric aligns more effectively with the spatial resolution of UAV imagery, where each pixel represents a portion of continuous vegetation, and minimizes the influence of vine spacing, pruning system, and canopy geometry. In previous studies, ground-truth datasets were typically derived from single-vine measurements, an approach that can introduce geometric inconsistencies in

Vertical Shoot Positioning (VSP) systems due to the mismatch between the canopy structure, composed by interactions and overlaps between adjacent plants, and its two-dimensional projection on orthomosaics. The extent of this misalignment varies with canopy density, vigor, and training system, but some spatial inaccuracy is unavoidable when individual vines are used as discrete sampling units. In contrast, canopy-segment-based sampling mitigates these distortions, providing a more coherent framework for developing scalable and generalizable UAV-based yield models.

In this context, our hypothesis was that to modify the ground-truth sampling strategy, from a plant-based to a linear approach, can significantly influence the accuracy of the functional relationships between RS-derived variables and yield. Accordingly, the aim of this study was to compare two ground-based sampling methods for yield data collection in VSP-trained vineyards and to assess their impact on the predictive performance in different frameworks. Specifically, three different frameworks were evaluated: linear correlation models, machine learning algorithms (Efficient Linear, SVM, Random Forest, and GPR) and a Bayesian inference framework.

Materials and methods

Experimental field description

The research was conducted during the growing season 2025 in an experimental site located in the Alcamo Protected Designation of Origin (PDO), in Sicily region (Italy; 37.92° N, 13.07° E; WGS 84; EPSG:4326) at an elevation of approximately 315 m a.s.l.). The area is characterized by a typical Mediterranean climate (Koeppen, W.,1936), with mild, wet winters and hot and dry summers. Historical climatic data indicate a mean annual temperature of 19 °C, with average monthly maxima reaching 31.4 °C in August and minima occurring in January. The mean annual precipitation is approximately 620–650 mm, most of which occurs between autumn and early spring. Weather data were continuously recorded by an EcoWitt WH6006 meteorological station installed near the experimental vineyard. The station includes integrated sensors for measuring air temperature, relative humidity, rainfall, solar radiation, wind speed and wind direction.

The site is characterized by a gently sloping terrain, with gradients not exceeding 12%, and covers a total area of 7.6 ha. The vineyard was planted in 2007 with *Vitis vinifera* L. cv.

Catarratto, grafted onto 1103 Paulsen rootstock. Vines are trained to a VSP system and pruned to a bilateral spur cordon, maintaining two buds per spur spaced at approximately 0.20 m. The planting layout follows a 2.20 inter-row $\times$ 1.00 m intra-row spacing, corresponding to a vine density of 4,545 vines ha⁻¹. The rows are oriented northeast–southwest (NE–SW), forming an angle of about 22° with respect to true north. The vineyard is managed under organic viticulture protocols, following ordinary agronomic and phytosanitary practices. Cultural operations include the application of composted manure, manual shoot positioning and pruning, and integrated pest management through sexual confusion techniques combined with the distribution of copper and sulphur-based treatments. Soil management consists of approximately five shallow tillage operations per year (to a depth of 0.10 m), aimed at controlling weeds, limiting surface evaporation, and preventing soil cracking. Nutrient inputs and plant protection measures were applied uniformly across the vineyard according to regional viticultural recommendations, ensuring balanced vegetative growth and high-quality fruit development. The site is equipped with a drip irrigation system, delivering an average seasonal water volume of approximately 600 m³ ha⁻¹ during the growing season to mitigate water stress under summer drought conditions.

Ground truth sampling methods

To appropriately capture the spatial variability within the experimental field and select the sampling locations, a comprehensive multisource spatial analysis was carried out.

Following the approach proposed by Canicatti et al. (2025a), multiple layers of historical information, collected between 2016 and 2025, were combined. Specifically, NDVI maps from Sentinel-2 satellite missions, were downloaded from the software Copernicus Open Access Hub (ESA) (<https://browser.dataspace.copernicus.eu/>). The time series was normalised and the per-pixel temporal standard deviation computed. Unstable areas were defined as pixels whose standard deviation exceeded the 80th percentile of the field-level distribution. Finally, a Jenks natural-breaks classification was applied to stable areas to partition the field into zones with consistent low-, medium, and high-vigour.

The areas identified by this approach were further validated by expert agronomic assessment and by multiple UAV-based multispectral surveys conducted between the 2021 and 2025.

Within each identified vigour zone, six spatially adjacent sampling blocks were delineated, this configuration was then replicated twice across the field, resulting in a total of 36 sampling blocks ($3 \text{ vigour levels} \times 6 \text{ blocks} \times 2 \text{ replicates}$).

The field sampling procedure was designed to characterize yield components relative to both per-meter and per-plant units (Figure 1). Specifically, two parallel spatial reference systems were established: one aligned with the projection of individual vines on the ground (Sampling plant unit), and one aligned with one-meter intervals along the row (Sampling meter unit).

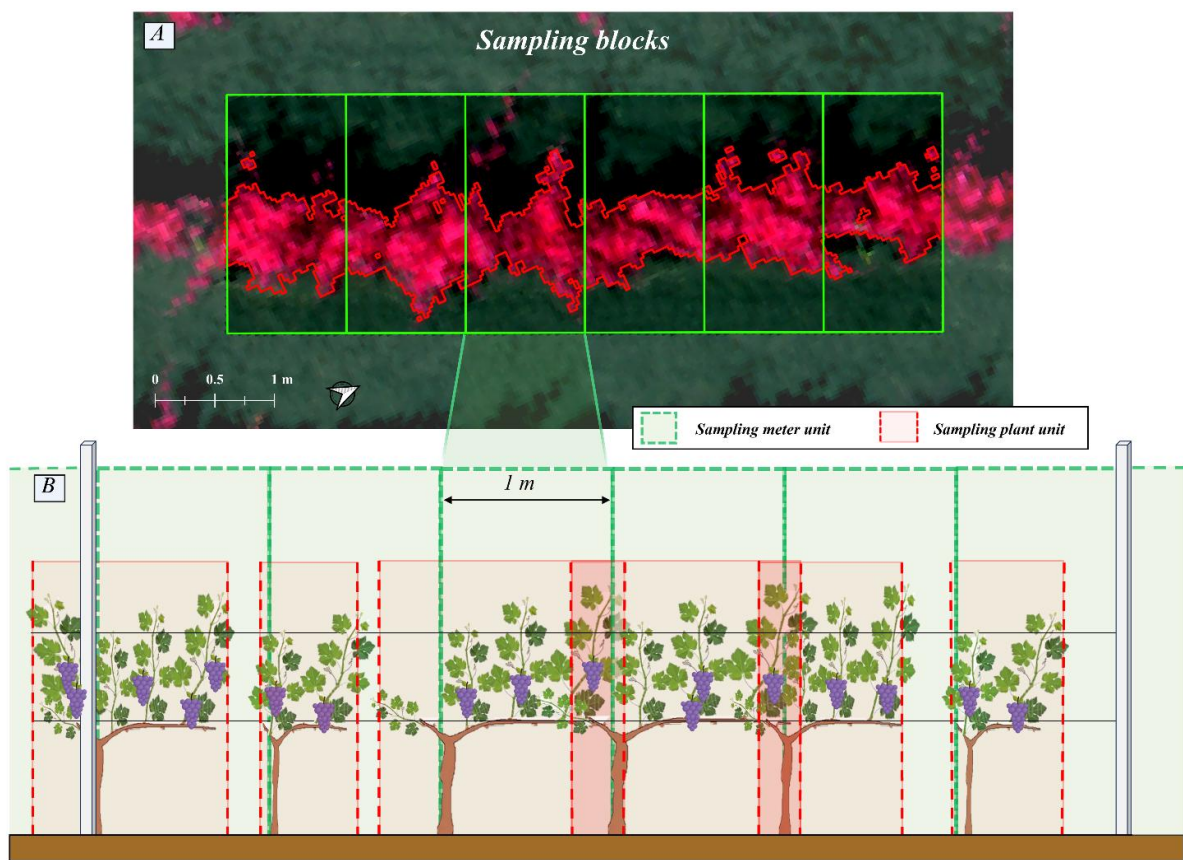


Fig. 1. Ground truth sampling design adopted in the vineyard. Sampling blocks configuration (A) and two sampling units (B) representation: (i) the sampling plant unit (red dashed lines), where measurements and yield components were collected individually for each vine, and (ii) the sampling meter unit (green dashed lines), corresponding to one-meter segments along the vine row.

For each delineated sampling segment, yield attributes were systematically collected. Specifically, the total fresh weight (defined here as yield), expressed as kg per meter or kg per vine, was measured using a calibrated field scale, and the number of grape bunches (expressed

as bunches per meter or per vine) was counted and recorded. Sampling was conducted sequentially along the rows to ensure a consistent representation of yield transitions across adjacent plants and block boundaries. The procedure began with the first plant of the first block, where production immediately outside the block boundary was harvested, followed by the yield inside the block from the first plant, potentially extending to part of the second plant, and then including the production of the first plant of the next block. This method ensured that each plant-meter encompassed four spatial contexts (outside, inside, overlapping, and adjacent). Once recorded data were processed to group the production at plant level and at the meter level.

UAV-based multispectral data acquisition and processing

The aerial surveys were conducted using a quadcopter system DJI Mavic 3 Multispectral (DJI, Shenzhen, China). The platform was equipped with a multispectral imaging system consisting of five sensors: one RGB (20 MP, 1/2" CMOS) and four monochromatic bands covering green (550 ± 16 nm), red (660 ± 14 nm), red-edge (735 ± 10 nm), and near-infrared (NIR, 790 ± 22 nm) wavelengths, each with 5 MP resolution. All sensors are mounted on a 3-axis stabilized gimbal to ensure image stability during flight operations. To achieve high-precision georeferencing, the UAV was equipped with an onboard GNSS mobile receiver, using RTK (real time kinematic). This configuration minimizes spatial errors in subsequent photogrammetric processing and vegetation index calculations. Data acquisition was performed around solar noon (12:30–13:30 local time) under optimal illumination conditions (clear sky, solar zenith angle $< 30^\circ$).

Flight operations were conducted on May 23 and August 5, corresponding to phenological stages of BBCH 73 and 85 respectively. The flight mission was planned to use DJI Terra software, with the following parameters. The UAV was operated at an altitude of 70 m above ground level (AGL), achieving a spatial resolution of 3.1 cm/pixel for multispectral imagery. Image acquisition used 75 % frontal overlap and 70 % side. The flight speed maintained at 3.2 m/s to optimize both operational efficiency and image quality. The flight path was set diagonally across the rows to improve the 3D reconstruction of the canopy and the orthomosaic reconstruction (Catania et al., 2023a). The multispectral imagery was processed using Agisoft Metashape Professional Edition ver. 1.7.3. as photogrammetric software. Image calibration was performed by placing a white Spectralon panel on the ground and the sunlight sensor of drone.

The panel reflectance was measured immediately before and after the flight using a spectroradiometer (Fieldspec2) already used in a previous study (Roma et al., 2023). Before the flights some Ground Control Points (GCPs) were uniformly distributed and georeferenced in the field. This step ensured high precision georeferencing of the multispectral imagery.

The Fc and NDVI were evaluated for each sampling point, corresponding to a vineyard block of 1 m in length and 2 m large. The positions of individual block and the boundaries of each block were georeferenced in the field using a Stonex S70 GPS receiver (Stonex S.r.l., Milan, Italy) and subsequently imported into QGIS to delimit the vines and blocks selected for the study. Vineyard canopy pixels were isolated using the U-Net ResNet101 semantic segmentation model, following the methodology described by Ferro et al. (2024), implemented in PyTorch, applied to 240×240 -pixel image tiles extracted from the digital orthophoto map (DOM). The image analysis process consists of an Encoder part and a Decoder part, through which all multiband DOM images were analysed to identify vineyard vegetation pixels, excluding those related to soil, spontaneous vegetation, or shadow influences. Image annotation was performed with Roboflow for labelling (Dwyer et al., 2024), and the dataset was split into training, validation, and test sets in a 70:10:10 ratio. Fc was determined for each meter as geometric ratio between the projected CA and the vineyard block, according to Roma et al. (2025). Subsequently, NDVI was calculated both at the single block scale and at the canopy-only level using the standard formula proposed by Rouse Jr et al. (1974). The resulting values were extracted for statistical assessment, enabling quantitative evaluation of canopy vigor and spatial variability. This structured protocol minimized interference from non-target surfaces while maintaining consistency with state-of-the-art UAV-based viticulture monitoring techniques.

Data analysis

Once the dataset was established, pairwise linear regressions were performed between the yield parameters and the UAV-derived variables to explore their individual relationships. In particular, the correlation between geometric and spectral canopy features. Specifically, pure canopy NDVI and mixed NDVI (soil and canopy) were used as spectral features, while Fc was used as a geometric feature. Subsequently, yield parameters were evaluated against combined spectral–geometric indicators, defined as product terms between NDVI (both canopy-only and block-level) and Fc.

Multiple ML algorithms were implemented using grape yield and RS survey data relating to BBCH73 stage to perform the yield estimation process in both sampling methods. Four models were selected based on their proven effectiveness for yield estimation in viticulture: (1) Efficient Linear Model, (2) Support Vector Machine (SVM), (3) Random Forests, representing an ensemble of trees approach, and (4) Gaussian Process Regression (GPR). ML framework was implemented using the Regression Learner toolbox in MATLAB (R2024b) environment. In addition, a randomized 5-fold cross-validation was performed to mitigate overfitting risk and ensure robust estimation of model performance.

A third modelling framework was then introduced, Bayesian inference modelling, given its dual advantages of being robust and capable of quantifying predictive uncertainty. The Bayesian analyses were performed in the R environment (R Core Team, 2024) using the *brms* package (Bürkner, 2018, 2017), which provides an interface to *Stan* (Carpenter et al., 2017), a probabilistic programming language designed for advanced Bayesian computation. Parameter estimation relied on the Hamiltonian Monte Carlo (HMC) algorithm, a gradient-based MCMC method that improves sampling efficiency and convergence. Specifically, the No-U-Turn Sampler (NUTS), a self-adaptive variant of HMC, was used to automatically tune step sizes and improve convergence for complex model structures (Bürkner, 2018, 2017; Carpenter et al., 2017; Ng'ombe and Lambert, 2021). The response variables modelled were “yield per vine” and “yield per meter”. Multiple Bayesian model configurations were tested to evaluate sensitivity to structural assumptions and predictor sets. The chosen covariates included NDVI at block and canopy-only level, Fc and their interaction. Given the limited availability of similar applications in the literature, standard priors were adopted to ensure model flexibility. Each model was fitted using four MCMC chains, each consisting of 10,000 iterations with 3,000 warm-up samples. Convergence was verified by ensuring all parameters had a Gelman–Rubin statistic $\hat{R} < 1.01$ and both bulk and tail effective sample sizes (ESS) exceeded 100 per chain (Vehtari et al., 2021).

Posterior distributions were summarized by reporting the 0.025, 0.50, and 0.975 quantiles, providing median parameter estimates and associated 95% credible intervals. The best-performing Bayesian model, identified through posterior predictive checks and information criteria, was subsequently applied to generate yield maps.

Model validation was subsequently performed by evaluating predictive performance under real field conditions. Specifically, model outputs at field scale were compared against the total yield

measured at harvest, enabling an assessment of predictive accuracy and robustness of the proposed modelling approach.

Performance evaluations

For model comparison, five key metrics were selected: Pearson correlation coefficient (r , eq.1), coefficient of determination (R^2 , eq.2), root mean square error (RMSE, eq.3), mean squared error (MSE, eq.4), and mean absolute error (MAE, eq.5), calculated as:

$$r = \frac{\sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2 \sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2}} \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (5)$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}$ represents the mean of the observed values and $\bar{\hat{y}}$ is the mean of the predicted values, and n is the total number of observations. These metrics provide complementary and interpretable measures of prediction accuracy and model error, allowing a robust comparison among different modelling approaches.

Results

The experimental design enabled a direct comparison between two yield-sampling strategies in VSP-trained vineyards, revealing their influence on model performance across different methodological approaches. The following sections detail the results from the three predictive frameworks and their ability to estimate yield under each sampling approach.

Linear relationships between yield and UAV-derived features

Across both phenological stages, linear regressions revealed consistent positive associations between UAV-derived spectral and geometrical metrics and yield (Fig.2-3; Tab.1), confirming the capacity of those features to reflect yield variability in VSP-trained vineyards. A clear difference was observed between the two sampling methods adopted for all the features considered. Scatterplots (Fig. 3 and 4) show consistent positive trends between yield and NDVI, canopy-only NDVI, Fc and their interaction terms, better trends are observed at BBCH 73 compared to BBCH 85. Points in high-vigour classes (HV) systematically occupied the upper portion of the yield distribution, whereas low-vigour points (LV) clustered at lower values.

At BBCH 73, linear-based sampling shows tight linear trends for NDVI and Fc, with the smallest error envelopes among single predictors (Fig.2). This is reflected in the performance metrics reported in Tab.1, where both NDVI and Fc reach $R^2 = 0.73$ (RMSE 0.34). NDVI Canopy remains significant but with lower performance. The plant-based sampling is visibly more dispersed for all three predictors, with R^2 ranging between 0.26 and 0.33 and RMSE ranging between 0.58 and 0.61.

At BBCH 85, the same trend persists with moderately wider bands (Fig.2). Per-meter fits remain significant across predictors, with Fc and NDVI again the most compact while NDVI Canopy is the least tight. Per-vine sampled fits panels remain weaker overall (Tab.1).

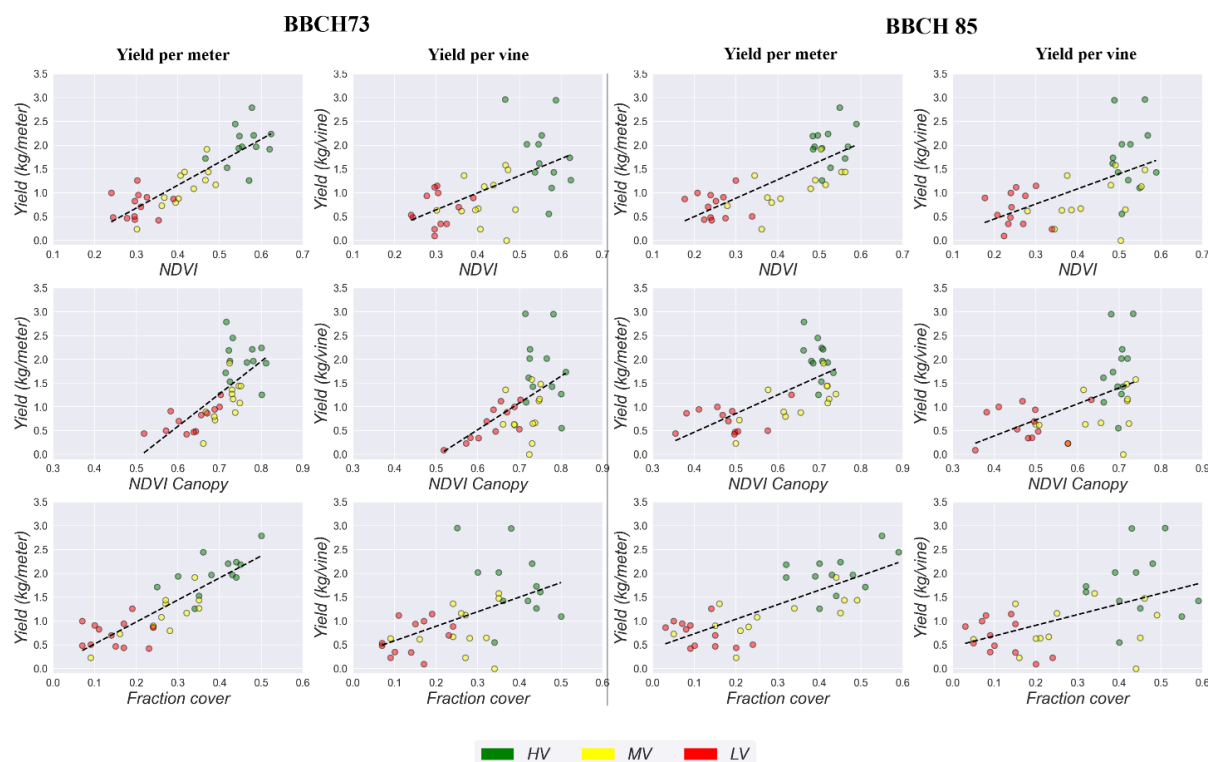


Fig. 2. Relationships between yield and UAV-based features acquired in BBCH 73 and BBCH 85. Scatterplots show the linear regressions between yield per meter and yield per vine against three UAV-derived indicators: NDVI, canopy NDVI, and Fc. Points are coloured according to plot's vigour classes: high vigour (HV, green), medium vigour (MV, yellow), and low vigour (LV, red).

Interaction terms display an overall stronger relationship with yield (Fig.3; Tab.1). In BBCH 73, $Fc \times NDVI$ delivers the top performance ($R^2 = 0.78$, $RMSE = 0.31$), exceeding single-predictor NDVI/Fc. At BBCH 85, the ranking is preserved with slightly broader dispersion; meter-based $Fc \times NDVI$ reaches $R^2 = 0.65$ ($RMSE = 0.38$), improving on NDVI at the same stage. In contrast, plant-based interaction fits remain modest and closely clustered around $R^2 \approx 0.28$ – 0.32 with $RMSE \approx 0.59$ – 0.60 , similar to the corresponding single-predictor results.

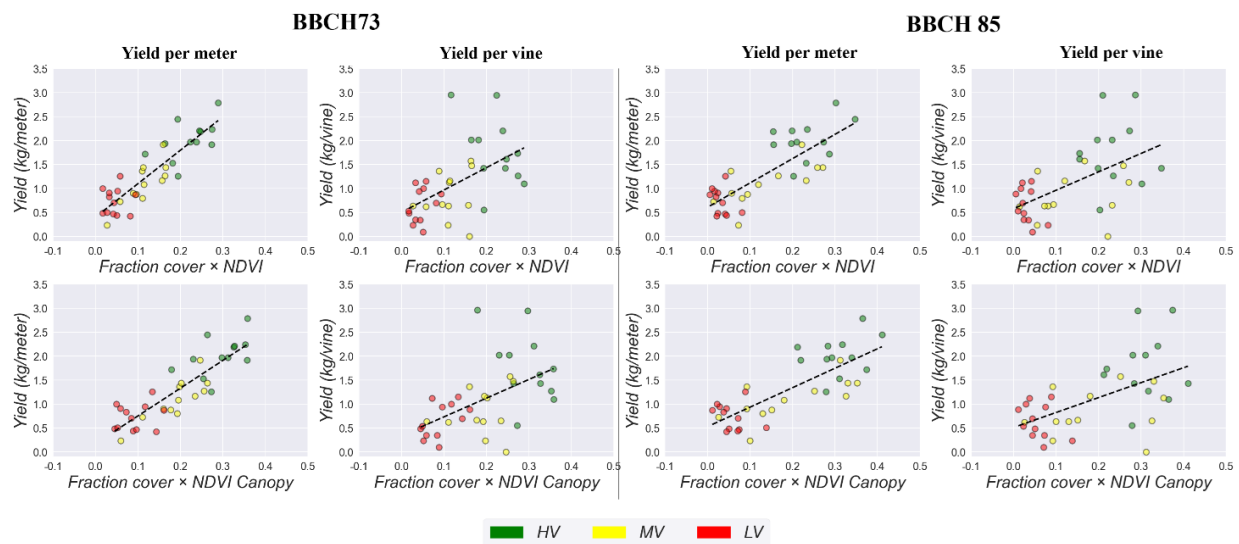


Fig. 3. Relationships between yield and UAV-based combined features acquired in BBCH 73 and 85. Scatterplots show the linear regressions between yield per meter (left column of each pair) and yield per vine (right column of each pair) against two composite vegetation indicators: $Fc \times NDVI$ canopy and $Fc \times NDVI$. Points are coloured according to plot's vigour classes: high vigour (HV, green), medium vigour (MV, yellow), and low vigour (LV, red).

Tab.1 Quantitative representation of performance of linear regression between yield and UAV-based features

Feature	Phenological stage	Sampling method	r	R ²	RMSE	MSE	MAE	Significance
NDVI	BBCH 73	Linear	0.85	0.73	0.34	0.11	0.27	***

NDVI Canopy	BBCH 85	Plant	0.58	0.33	0.58	0.34	0.44	***	
		Linear	0.77	0.59	0.42	0.17	0.36	***	
		Plant	0.57	0.33	0.58	0.34	0.46	***	
	BBCH 73	Linear	0.70	0.48	0.47	0.22	0.37	***	
		Plant	0.52	0.27	0.61	0.37	0.43	**	
	BBCH 85	Linear	0.69	0.47	0.47	0.22	0.40	***	
		Plant	0.54	0.29	0.60	0.36	0.44	**	
	Fraction cover	BBCH 73	Linear	0.86	0.73	0.34	0.11	0.28	***
			Plant	0.51	0.26	0.61	0.37	0.44	**
		BBCH 85	Linear	0.79	0.63	0.39	0.16	0.34	***
			Plant	0.55	0.30	0.60	0.36	0.47	**
	Fraction cover × NDVI	BBCH 73	Linear	0.88	0.78	0.31	0.09	0.25	***
			Plant	0.54	0.29	0.60	0.36	0.44	**
		BBCH 85	Linear	0.81	0.65	0.38	0.15	0.33	***
			Plant	0.56	0.31	0.59	0.35	0.47	**
Fraction cover × NDVI Canopy	BBCH 73	Linear	0.86	0.75	0.33	0.11	0.27	***	
		Plant	0.53	0.28	0.60	0.37	0.42	**	
	BBCH 85	Linear	0.80	0.63	0.39	0.15	0.34	***	
		Plant	0.56	0.32	0.59	0.35	0.46	**	

*** $p < 0.001$ / ** $p < 0.01$ / * $p < 0.05$ / n.s. $p \geq 0.05$

Linear regression between number of bunches and UAV-derived features

Across both stages, regressions between number of clusters and UAV features were positive but weaker than for yield, with meter-based fits improving performance compared to plant-based sampling (Fig.4; Tab.2). At BBCH 73, single predictors in meter-based panels showed low correlations: Fc was the strongest among them ($R^2 \approx 0.25$, RMSE ≈ 1.9 clusters), while NDVI and NDVI Canopy were lower ($R^2 \approx 0.18$, RMSE ≈ 2.0). For plant-based sampling, relations were generally negligible ($R^2 \leq 0.06$; RMSE ≈ 3.0 ; mostly n.s.). At BBCH 85, the pattern persisted (Fig.4).

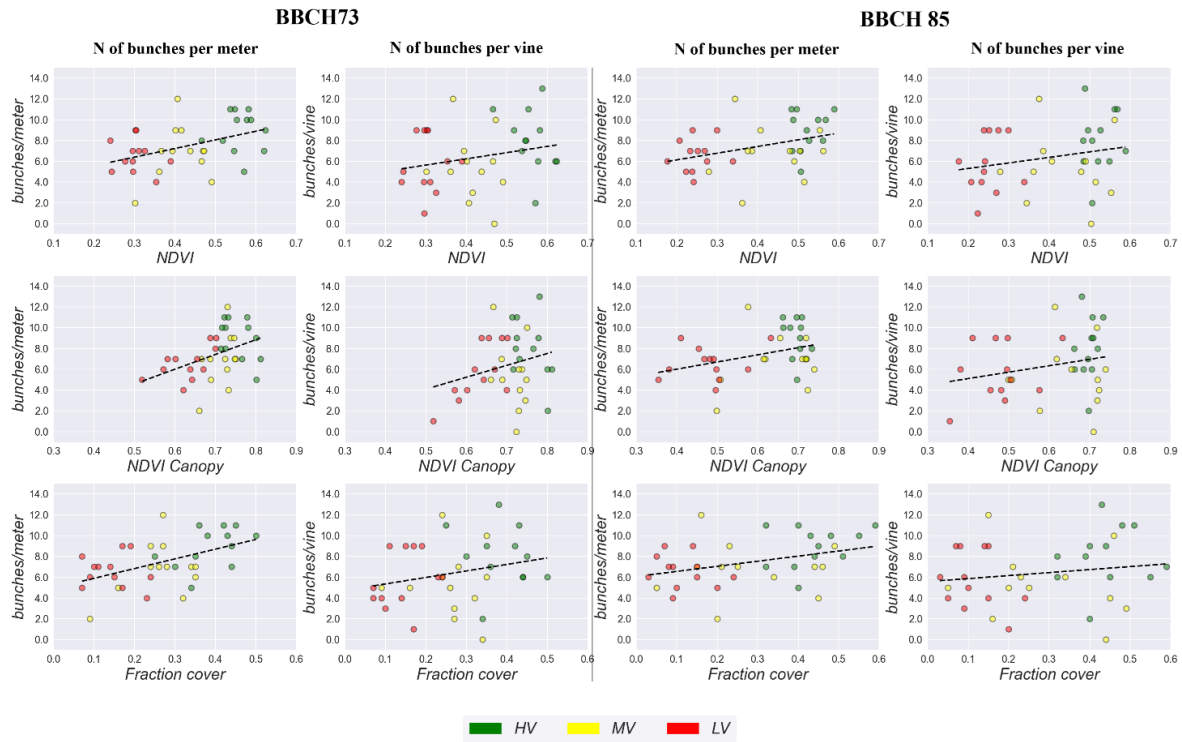


Fig 4. Relationships between the number of grape clusters and UAV-based features acquired in BBCH 73 and 85. Scatterplots show the linear regressions between the number of grape clusters per meter and per plant against three vegetation indicators: NDVI, canopy NDVI, and Fc. Points are coloured according to plot's vigour classes: high vigour (HV, green), medium vigour (MV, yellow), and low vigour (LV, red).

Tab. 2 Quantitative representation of performance of linear regression between the number of grape clusters and UAV-based features

Feature	Phenological stage	Sampling method	r	R ²	RMSE	MSE	MAE	Significance
NDVI	BBCH 73	Linear	0.43	0.18	2.02	4.06	1.59	*
		Plant	0.22	0.05	3.00	8.99	2.40	n.s.
	BBCH 85	Linear	0.37	0.14	2.07	4.28	1.65	*
		Plant	0.22	0.05	3.00	8.99	2.44	n.s.
NDVI Canopy	BBCH 73	Linear	0.42	0.18	2.02	4.09	1.60	*
		Plant	0.25	0.06	2.98	8.89	2.41	n.s.
	BBCH 85	Linear	0.35	0.12	2.09	4.35	1.68	*
		Plant	0.23	0.05	2.99	8.96	2.43	n.s.
Fraction cover	BBCH 73	Linear	0.50	0.25	1.93	3.72	1.56	**
		Plant	0.24	0.06	2.98	8.90	2.35	n.s.
	BBCH 85	Linear	0.39	0.15	2.06	4.23	1.59	*
		Plant	0.21	0.04	3.01	9.06	2.44	n.s.

Fraction cover × NDVI	BBCH 73	Linear	0.49	0.24	1.95	3.79	1.55	**
		Plant	0.24	0.06	2.99	8.93	2.38	n.s.
	BBCH 85	Linear	0.39	0.15	2.05	4.20	1.59	*
		Plant	0.21	0.04	3.01	9.05	2.44	n.s.
Fraction cover × NDVI Canopy	BBCH 73	Linear	0.50	0.25	1.93	3.72	1.57	**
		Plant	0.24	0.06	2.98	8.91	2.36	n.s.
	BBCH 85	Linear	0.38	0.14	2.06	4.25	1.61	*
		Plant	0.20	0.04	3.01	9.07	2.44	n.s.

*** $p < 0.001$ / ** $p < 0.01$ / * $p < 0.05$ / n.s. $p \geq 0.05$

Composite indicators showed limited gains over single predictors for number of bunch cluster (Tab.2). At BBCH 73, $Fc \times NDVI$ and $Fc \times NDVI$ Canopy in meter-based sampling achieved $R^2 \approx 0.24$ – 0.25 (RMSE ≈ 1.93 – 1.95). At BBCH 85, composites remained low ($R^2 \approx 0.14$ – 0.15 , RMSE ≈ 2.03 – 2.06), and plant-based interactions were largely non-significant (Fig. 5).

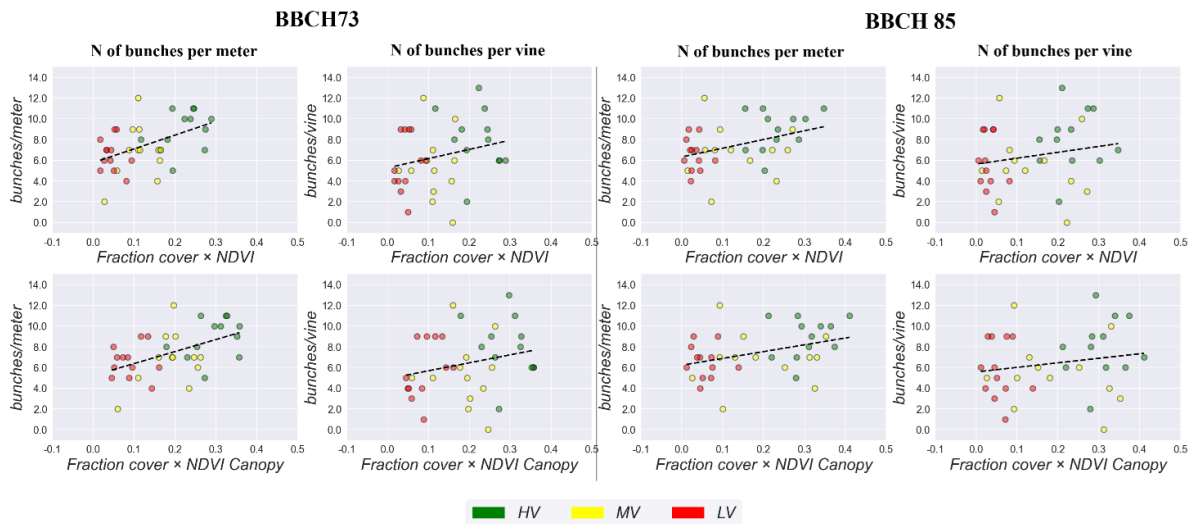


Fig. 5. Relationships between the number of grape clusters and UAV-based combined features acquired in BBCH 73 and 85. Scatterplots show the linear regressions between the number of grape clusters per meter and per plant against two composite vegetation indicators: $Fc \times NDVI$ canopy and $Fc \times NDVI$. Points are coloured according to plot's vigour classes: high vigour (HV, green), medium vigour (MV, yellow), and low vigour (LV, red).

Machine learning models performance

Fig. 6 shows the results of the comparative performance of the four ML algorithms for yield estimation under the two sampling strategies, linear based and plant based.

Across all algorithms, linear-based sampling outperformed plant-based sampling in all metrics. For the linear sampling, metrics result in a narrow, high range ($R^2 = 0.70$ – 0.76 , $RMSE = 0.33$ – 0.37), while plant-based sampling remained in lower and more dispersed ranges ($R^2 = 0.15$ – 0.27 , $RMSE = 0.62$ – 0.67). The best scores were obtained by the Efficient Linear and SVM models under meter-based sampling (both $R^2 = 0.76$, $RMSE = 0.33$, $MSE = 0.11$, $MAE = 0.28$), closely followed by GPR. Under plant-based sampling, none of the algorithms achieved competitive accuracy; SVM and Efficient Linear were marginally higher ($R^2 \approx 0.24$ – 0.27 kg m^{-1}) than Ensemble and GPR ($R^2 \approx 0.15$ – 0.17).

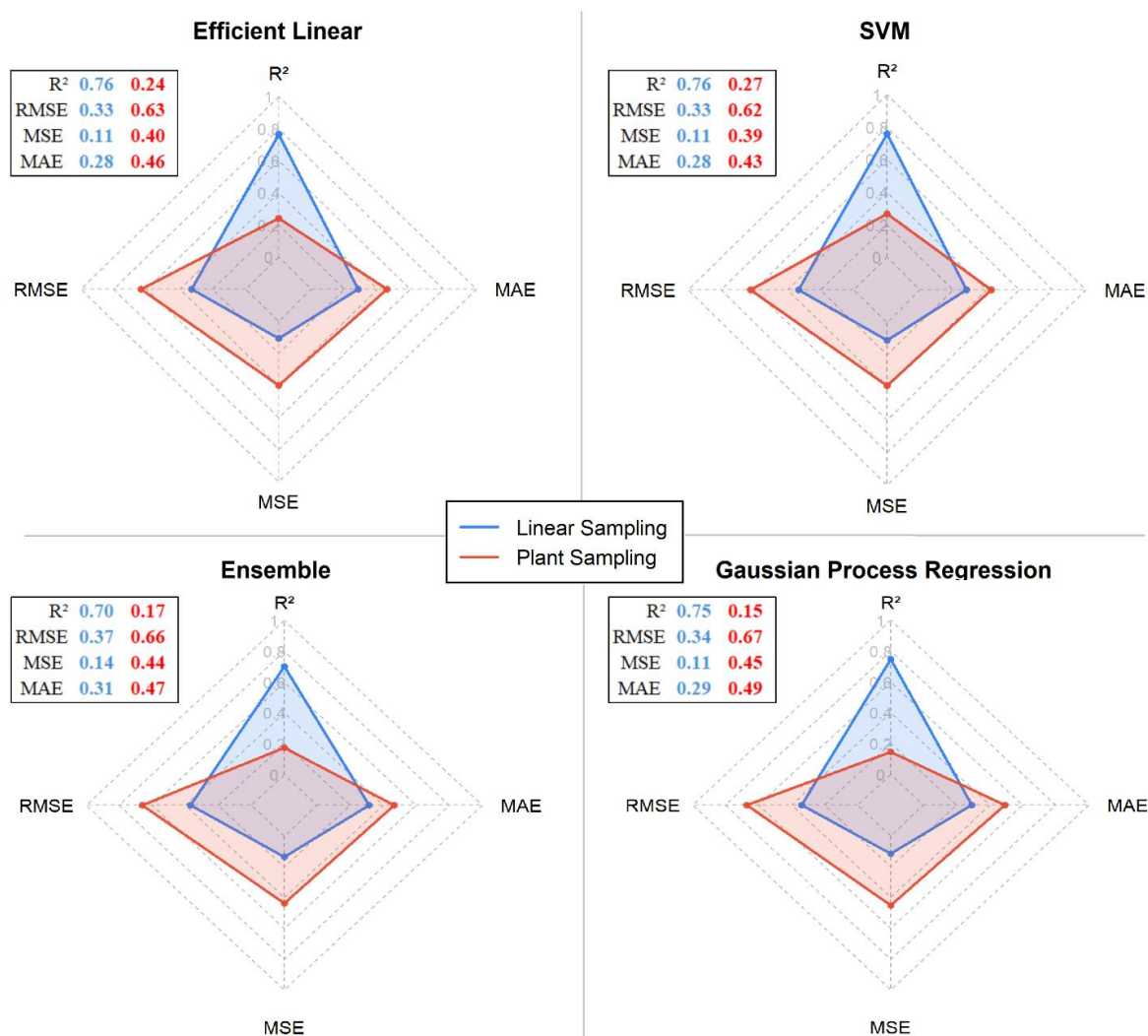


Fig. 6. Comparison between Linear Sampling (blue) and Plant Sampling (red) across the four ML models: Efficient Linear, SVM, Ensemble, and GPR. Radar plots display the performance for the evaluated metrics: R^2 , RMSE, MAE, and MSE.

Performance of Bayesian modelling

Bayesian modelling based on linear sampled data showed strong predictive performance, with a coefficient of determination R^2 of 0.84, a RMSE of 0.26 kg m⁻¹ and a MAE equal to 0.22 kg m⁻¹ (Figure 7a). The predicted posterior medians and the observed yield values are closely aligned. Most observations cluster symmetrically along the regression line. The uncertainty bar, posterior standard deviations, remain relatively narrow and consistent. Minor deviations are observed at the upper end of the yield distribution, while slight underestimations are present for lower values. Conversely, Bayesian modelling trained using yield data expressed per vine showed substantially lower predictive performance (Figure 7b). The model achieved an R^2 of 0.41, with an RMSE of 0.55 kg vine⁻¹. The data points are more dispersed around the 1:1 line, with broader 95% credible intervals. In particular, over- and underestimation patterns are visible at both extremes of the yield range.

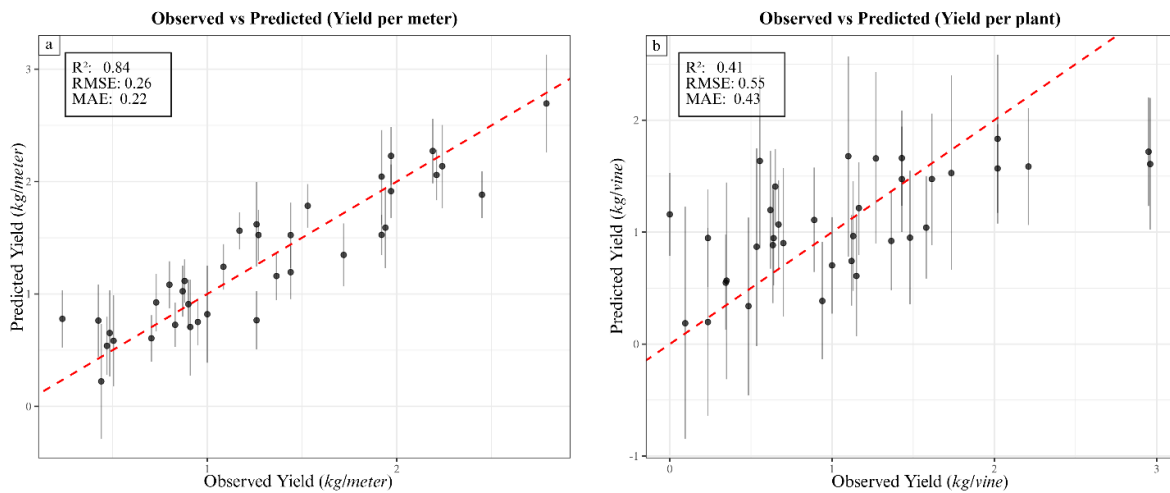


Fig. 7. Observed versus predicted yield values obtained from the Bayesian inference model for yield per meter (kg/meter) (a) and yield per plant (kg/vine) (b). Black dots represent the posterior medians of the predicted yield, with vertical bars indicating the 95% credible intervals. The red dashed line represents the 1:1 relationship. Model performance metrics (R^2 , RMSE and MAE) are reported in each panel.

Spatial variability of yield and uncertainty analysis

The yield prediction map in Fig.8A revealed marked spatial variability across the vineyard, with estimated values ranging from below 1.0 kg·m⁻¹ to over 3 kg·m⁻¹. The highest predicted yields

were concentrated in the southern and central-eastern sectors, while lower-yielding zones were predominantly located in the northern portion of the field.

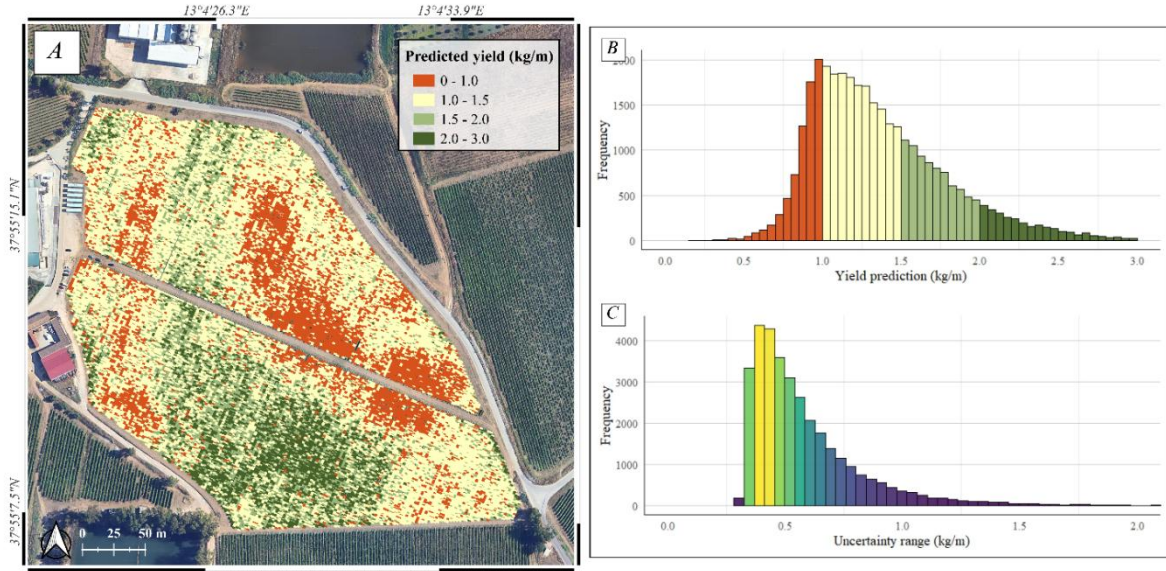


Fig. 8. Spatial distribution of predicted grapevine yield (kg/m) across the experimental vineyard (A) and corresponding frequency distributions (B). Histogram of yield predictions (kg/m) highlighting a right-skewed distribution. Histogram of prediction uncertainty (C) (kg/m), showing that most estimates exhibited low uncertainty (kg/m).

The overall distribution of predicted yield followed a right-skewed pattern (Fig. 8B) with a dominant class between 1.0 and 1.5 kg·m⁻¹. The uncertainty analysis (Fig. 8C) indicates that most predictions exhibited an uncertainty below 0.6 kg·m⁻¹, confirming a satisfactory model reliability at the intra-vineyard scale. The observed yield of the experimental vineyard was 6.54 t·ha⁻¹, corresponding to an average of 1.43 kg·plant⁻¹. Among the two sampling strategies evaluated, the linear sampling approach provided a more accurate estimation of yield per hectare than the plant-based method. Specifically, the linear sampling underestimated the actual yield by only 5.41%, predicting 6.19 t·ha⁻¹ (1.36 kg·plant⁻¹), whereas the plant-based method underestimated the total yield by 17.6%, corresponding 5.39 t·ha⁻¹ (1.18 kg·plant⁻¹).

Discussions

The findings show that the definition of the ground-truth unit markedly conditions the accuracy of RS-based yield modelling in VSP vineyards. Across simple linear fits, ML and bayesian models, the linear-based sampled data outperformed the plant-based sampling approach, with

consistently higher R^2 and lower errors. The one-meter segments preserve the geometric continuity of the canopy wall and align better with the UAV-ground projection. This reduces the effects of edge overlap and systematic misalignment that occur when a single grapevine is treated as an isolated unit and subsequently associated with RS data. In fact, the linear method reflects spatial continuity in VSP systems more accurately, since the canopy is a continuous productive unit rather than a discrete system of individual plants.

The results obtained in this study address a key methodological limitation previously identified in UAV-based vineyard yield estimation. Earlier research demonstrated the potential of RS imagery to predict yield with high accuracy. However, these studies relied predominantly on vine-based ground-truth data, which inherently limits model generalization across different training systems and canopy architectures (Ballesteros et al., 2020a; Di Gennaro et al., 2019b; López-García et al., 2022). In vine-level sampling, the predictive relationship between RS canopy descriptors and actual yield is strongly influenced by pruning configuration, vine geometry, and canopy discontinuity, all of which vary considerably between vineyards (Carrillo et al., 2016; Gatti et al., 2017; Keller et al., 2010).

In this study the bivariate analyses showed that, for linear-based sampled data, yield was strictly related to canopy geometry and spectral response. Composite predictors such as $Fc \times NDVI$ and $Fc \times NDVI$ canopy provided the best results, with more noticeable gains at the beginning of the season (BBCH 73), when canopies reach maximum vegetative growth. Meanwhile, the weak relationships observed for the number of grape clusters suggest the presence of complex physiological mechanisms controlling plant cluster size that are not fully detectable by remote sensing alone. These findings align with prior evidence that fusing geometric and spectral features improves predictive power for functional relationships with yield and other parameters (Ballesteros et al., 2020b); in another example, Campos et al. (Campos et al., 2021b) reported improvements when NDVI was combined with a canopy-projection metric (their analogue of Fc) to relate RS to canopy volume.

The results obtained in this study help to provide context for the reason that data referring to individual plants often show strong correlations, despite the high geometric misalignments likely in VSP systems. In fact, some studies did not perform validation at the individual vine level, but aggregated vines into short sections or plots to suppress sampling errors. For example, Carrillo et al. (Carrillo et al., 2016) and Ballesteros et al. (Ballesteros et al., 2020b) aggregated five consecutive vines and plots of ~18 vines, respectively, into a single sampling unit. In line

with this basis, in a previous analysis, the authors compared sampling per plant with contiguous blocks of six vines and found that the block strategy was more accurate and less prone to bias (Canicattì et al., 2025b). Others approaches compare a “representative” vine to plot-level RS features (López-García et al., 2022). While effective, these strategies do not fully take the advantage of UAV spatial resolution and increase ground effort, as large numbers of vines should be harvested or counted to stabilize the signal.

ML outcomes corroborate a model-agnostic benefit for the meter-based sampling design. Across distinct algorithmic families, meter-based ground truth yielded systematically higher R^2 and lower RMSE/MAE than per-plant sampling, indicating that the improvement derives from reduced label noise via better footprint congruence, rather than any algorithm-specific effect. These patterns are consistent with those in Matese and Di Gennaro (Matese and Di Gennaro, 2021), showing that coupling NDVI with canopy thickness (a geometric descriptor similar to Fc) improved fits; in a 5-fold cross-validation comparison, Random Forest performed best (approximately $R^2 \approx 0.73$ with spectral+geometric inputs), with most algorithms in the $R^2 \approx 0.65$ – 0.70 range.

The Bayesian posterior results highlighted a clear gap between yield per meter ($R^2 \approx 0.83$; RMSE ≈ 0.26 ; narrow credible intervals) and yield per plant ($R^2 \approx 0.41$; RMSE ≈ 0.55 ; wider intervals), reinforcing that the linear unit reduces observation noise and propagates less uncertainty. From a modeling perspective, yield per linear meter enhances the structural coherence between field and RS data, improving the capacity of Bayesian modeling frameworks to capture spatial dependencies and reduce posterior uncertainty. The resulting models exhibit smoother and more consistent predictive behaviour across different vigor zones and canopy densities. Compared to the other study on Bayesian yield mapping reported in Canicattì et al. (Canicattì et al., 2025b) the linear-based method tested in this study increases the spatial resolution of the prediction, reaching 1 meter resolution, a very useful information in all the condition where high performance evaluation is needed, like in plot experiment or in fragmented agricultural situations. Validation against total field production confirmed the generalizability of the findings. A more robust and transferable sampling framework that mitigates the geometric biases of vine-based protocols may also accelerate the broader adoption of PV (Santesteban et al., 2013). Taken together, these findings contribute to closing an existing research gap by demonstrating that the sampling unit itself plays a pivotal role in the reliability and generalization of UAV-based yield models.

Limitations and future prospectives

The framework presented in this study demonstrated good capabilities for improving yield mapping in VSP vineyards using UAV multispectral data. Nevertheless, some limitations persist, alongside numerous avenues for future development. This study isolates how the definition of the ground-truth unit (plant- vs meter-based) conditions RS–yield relationships in VSP vineyards. Its generalizability, however, is bounded by the experimental domain: trials were conducted within a single experimental field, while the relationships between spectral/geometric predictors and yield are physiologically sensitive to architectural features, trunk height, cordon height, row spacing, canopy thickness, pruning style. Those field condition modulate the pixel-scale thickness of canopy and background and, hence, the resulting spectral signal. Notwithstanding these constraints, the linear-based sampling showed consistent gains over plant-based sampling across linear, ML, and Bayesian frameworks, indicating that the geometric rationale behind a linear unit reduces sampling bias and improves generalizability. Still, this study’s aim does not claim a universal predictor; rather, it provides a sampling protocol that improves accuracy and correctness of RS-based yield estimation.

Future work should expand the experimental field conditions in a various cultivar, multi-region, multi-year experiments and explicitly test alternative wall-trained systems beyond grapevine, including super-high-density (SHD) olives, apple fruiting-walls, and other hedgerow orchards. Methodologically, a Bayesian hierarchical framework could be next step to pool across genotype, training system, site, and year, while accommodating spatial effects and quantifying the uncertainty; this would allow principled sharing of information across trials, potentially reducing the number of calibration points in new trials. Predictor space could be broadened to include 3D structural metrics (e.g., LiDAR-derived height/porosity/volume) and thermal or multi-temporal descriptors. Finally, the linear sampling logic should be evaluated for other targets beyond yield, like biomass, pruning weight, LAI, or nitrogen status, to test whether the same geometric alignment consistently improves functional relationships across traits and phenological stages.

Conclusions

The results of this research demonstrate that the choice of ground-truth method is a first-order driver of accuracy in RS-based yield modelling in VSP-trained vineyards. From ground

sampling that delimits contiguous linear segments rather than individual grape varieties, it has been possible to systematically improve performance on tested models, showing higher R^2 values. Meter-based sampling preserves the geometric continuity of the canopy wall characteristic of VSP systems, whereas vine-level units introduce misalignment and geometric bias. Bivariate analyses confirmed that yield relates tightly to canopy features, with composite geometric/spectral predictors performing best, especially at BBCH 73. Bayesian inference further quantified the gain of yield per meter sampling method, and whole-field yield totals corroborated external validity. While these findings were obtained in VSP vineyards, future research should test transferability to alternative training systems, environments and cultivars. Overall, redefining the reference unit as contiguous canopy segments provides a sampling framework that systematically improves the accuracy and robustness of UAV-based yield models and enables their use in the PV sector.

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Sustainable soil management in viticulture: a case study

Abstract

Soil degradation in Mediterranean vineyards, decreasing from intensive land management, poses challenges as erosion, compaction, and biodiversity loss. Advanced technologies fulfil a pivotal role in precise and sustainable soil management, proving in the preservation of soil quality and reducing negative impacts on biodiversity and the environment. Multispectral data can be used to identify areas with different crop growth levels and optimise resource distribution in vineyards. Indirectly, they support identification of zones susceptible to lower soil organic carbon (SOC) content or soil compaction, both of which are recognised to have a critical impact on root elongation and overall soil fertility. The aim of this study was to apply an innovative approach to evaluate the effect of soil variability in an organic vineyard in Sicily (Italy). This method involved historical satellite multispectral data, on season UAV multispectral data and soil analysis. The study was conducted at the beginning of the growing season (November 2021, T0) and followed until the end of the vineyard growing season (September 2022, T1). During the crop cycle, various vineyard growth parameters were monitored, including the shoot pruning weight (SPW); shoot length (SL); total leaf area (TLA); grape yield per plant (kg/vine); and grapes total soluble solids (TSS) content. During vineyard's winter dormancy, a soil treatment, involving the seeding of a cover crop (CC) (*Vicia faba* var. *minor*), was carried out. CC was mulched into the soil during spring season. Fresh weight and dry weight measurements of CC biomass were recorded. Among the soil parameters, soil penetration resistance (PR) was considered, evaluated at two depths (PR1= 0-30 cm; PR2= 30-60 cm), and the SOC was measured. Soil conditions, such as penetration resistance and SOC, significantly influenced cover crop vigor class and consequently overall vineyard growth. This approach has been useful in understanding the dynamics of the soil-plant-atmosphere system and can greatly benefit vineyard nutritional management.

Keywords: Precision viticulture, UAVs, remote sensing, soil organic carbon; soil penetration resistance.

Introduction

Modern viticulture requires an integrated understanding of the interactions between vines, soil, climate, and agricultural practices to produce high-quality grapes. An in-depth analysis of these dynamics is essential for optimizing agricultural practices, promoting environmental sustainability, and maintaining high oenological standards. As viticulture evolves, the emphasis on environmental sustainability has become paramount, highlighting the adverse effects traditional practices can have on soil health, water resources, and biodiversity (Giffard et al., 2022). A promising strategy to enhance sustainability is the use of cover crops between vineyard rows. This practice improves soil structure, increases organic carbon (SOC), reduces bulk density (SBD), and mitigates soil erosion (Cataldo et al., 2020). Nitrogen uptake by plants depends on the amount of available nitrogen in the soil and the management techniques adopted, influencing parameters such as shoot growth, berry growth, grape yield and quality, and overall vine vigor. Plant vigor is a fundamental indicator of vine growth and health (Ferro et al., 2023). An accurate estimate of vigor is one of the most valued aspects in precision viticulture. Vigor is influenced by many factors, some more variable in short term, such as the availability of water and nutrients, and others more stable, such as the genotypes type of planting, vineyard exposure and slope, macroclimate of the area, and soil characteristics (Auslander et al., 2003; Maestrini and Basso, 2018).

Normalized Difference Vegetation Index (NDVI) is widely used to monitor crop growth and the spatiotemporal variability of crop parameters, including vigor. Applications of remote sensing cover various sectors, including nutrition, irrigation, and plant protection (Catania et al., 2023a; Roma et al., 2024a, 2023b). Some approaches apply remote sensing techniques directly to cover crops, considering them bio-indicators of soil conditions. This approach, proposed by several researchers including Futerman et al. (Futerman et al., 2023), has led to the development of prescription maps for fertilization based on the variability of cover crop vigor. The main remote sensing technologies include unmanned aerial vehicles (UAV) and satellite platforms. Drones, representative of precision agriculture, are used for spraying operations and monitoring, providing high spatial resolution images (Canicattì and Vallone, 2024; Hafeez et al., 2023). Satellites, on the other hand, provide historical data useful for identifying

management zones (ZM). By combining the benefits of both platforms, increasingly accurate management recommendations can be developed (Clapp and Ruder, 2020; Sozzi et al., 2020).

The objective of this study is to use an innovative approach to identify spatiotemporal soil patterns and identify management zones within a vineyard before the start of the growing season.

Materials and methods

Experimental site

The study was conducted in a 16-year-old vineyard located in Camporeale, Sicily (Palermo, Italy), at Tenuta Rapitalà (37°55'12 "N and 13°04'27 "E) during the 2021-2022 season. This region is characterized by a semi-arid Mediterranean climate. The 8-ha⁻¹ vineyard was planted in 2007. The training system is a double cordon spur and vineyard layout consists of row spacing of 2.40 m, with the vines spaced approximately 1 m apart within each row. Field management follows standard agronomic practices of the area, including a drip irrigation system. The experimental area features irregular topography with elevations ranging from 340 to 369 meters above sea level. Due to the terrain's irregularity and soil properties, the vineyard exhibits heterogeneous vigor variability. Soil management includes the sowing of a legume species (*Vicia fava* L.), with an amount of 90 kg ha⁻¹, as cover crop in early winter (mid-November), which is mechanically incorporated into the soil in spring (mid-April).

Historical maps analysis

Historical spectral maps from 2016 to 2021 were utilized to determine the variability in vine vigor over different years. This period was divided into cover crop presence (DOY 305-63) and vineyard presence (DOY 121-240) for each year, adapting the approach described by Cammarano (Cammarano et al., 2021). The maps were derived from Sentinel-2 satellite missions, in particular band 4 (Reflectance in Red) and 8 (Reflectance in Nir) was used to calculate NDVI. Maps were downloaded using the Copernicus (ESA) (<https://browser.dataspace.copernicus.eu/>). Map processing, data extraction, and analysis were performed using Python and GIS environments. The NDVI maps were normalized, and the standard deviation for each pixel was calculated. Unstable zones were defined as pixels with a

standard deviation exceeding the 80th percentile. The analysis of historical spectral data, led to the division of the field into four management zones: high vigor (HV) (Cluster 3), medium vigor (MV) (Cluster 2), low vigor (LV) (Cluster 2), and unstable (U) (Cluster 0). These zones allowed for the identification of specific points for soil and plant sampling. A total of 16 points were sampled for yield and soil analysis, with the number of points determined by the relative area of each zone.

UAV and ground surveys

The sampling campaign was conducted during the 2021-22 growing season. The study spanned from the beginning of the growing season in November 2021 (T0) to the end of the vineyard season in September 2022 (T1). During the winter dormancy period, on day of the year (DOY) 63, the spatial variability of cover crops was assessed using agronomic and spectral surveys. Additional surveys were carried out during the vineyard season on DOY 169 and 226. The variability in vine vigor was monitored using multispectral images. These were captured using a Phantom4 Multispectral drone (DJI, China), equipped with a multispectral camera that includes one RGB sensor and five monochrome 2.08 MP sensors. These data were correlated with physical and chemical soil measurements and plant growth metrics to determine the impact of environmental variables on vineyard productivity. Throughout the crop cycle, various vineyard growth parameters were monitored, including shoot pruning weight (SPW), shoot length (SL), total leaf area (TLA), grape yield per plant (kg/vine), and total soluble solids (TSS) content of the grapes. Fresh weight and dry weight measurements of cover crop biomass were also recorded.

Soil analysis

The soils are classified as Vertisols with typical characteristics of clay soils (FAO, 2006). The soil has a clayey texture with a pH of 7.66 and a cation exchange capacity of 0.19 dS m⁻¹. Soil samples were collected in 2022, at the end of winter. Soil water content (SWC) was determined by the weight difference between fresh and dried samples. Soil penetration resistance (PR) was assessed up at two depths (PR1 = 0-30 cm; PR2 = 30-60 cm) using a portable digital penetrometer (Eijkelkamp Penetrologger model 06.15). Chemical analyses of the soil were

conducted on air-dried samples sieved to 2 mm. Soil organic carbon (SOC) was determined using the dichromate digestion and Kjeldahl methods, respectively.

Statistical analysis

The data collected from remote sensing platform and ground sampling were processed and subjected to statistical analysis in Rstudio software (R Core Team, 2024). Descriptive statistics (mean, maximum, minimum, standard deviation) were first calculated, followed by an analysis of variance (ANOVA) and Tukey's multiple comparison tests.

Results and discussions

Historical map processing and temporal patterns analysis

The analysis of spectral data collected between 2016 and 2022 revealed significant spatial variability within the vineyard, with a tendency to repeat over time (Fig. 1).

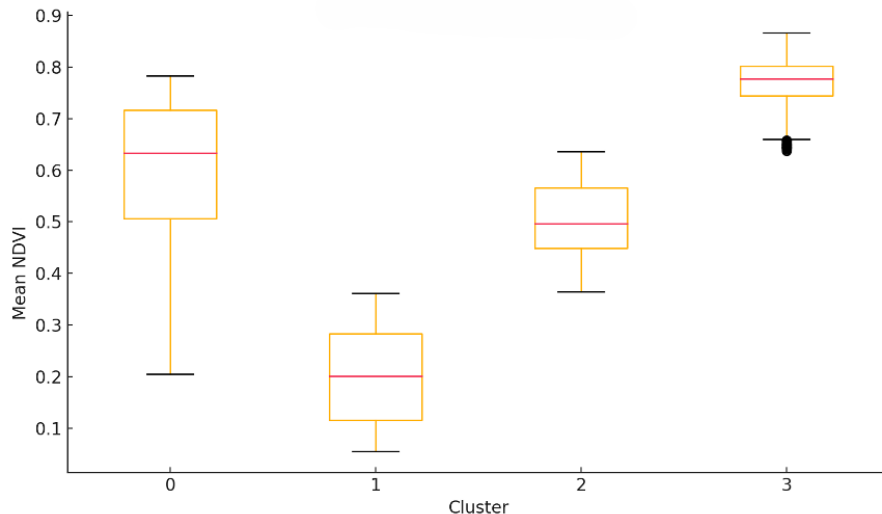


Fig. 1. Box-plot representing NDVI range values belonging to each cluster, specifically cluster 0 represents unstable zones, cluster 1 represents low vigor zones, cluster 2 represents medium vigor zones, and cluster 3 represents high vigor zones.

NDVI maps showed that the spectral response exhibits a consistent trend over the years, graphically represented by the vigour Stability Map (Fig. 2). Areas with greater variability were highlighted in red, indicating a tendency for significant changes. To investigate the causes of

this variability, detailed sampling was planned. Sampling points were selected for each zone category, and significant differences in soil properties were identified.

The data allowed for the classification of the vineyard into four main macroareas (Fig. 2): areas with consistently (HV), which maintain consistently high levels of vegetative vigor (Fig.1, Cluster 3); areas with consistently (MV), which have moderate and constant levels of vegetative vigor over time (Fig.1, Cluster 2); areas with consistently (LV), characterized by consistently low levels of vegetative vigor (Fig.1, Cluster 1); and unstable areas (U), identified by pixels with a standard deviation above the 80th percentile (0.0814) (Fig. 1, Cluster 0).

This facilitated the identification of sampling points for each category, and the results confirmed differences in the physical and chemical characteristics of the soil.

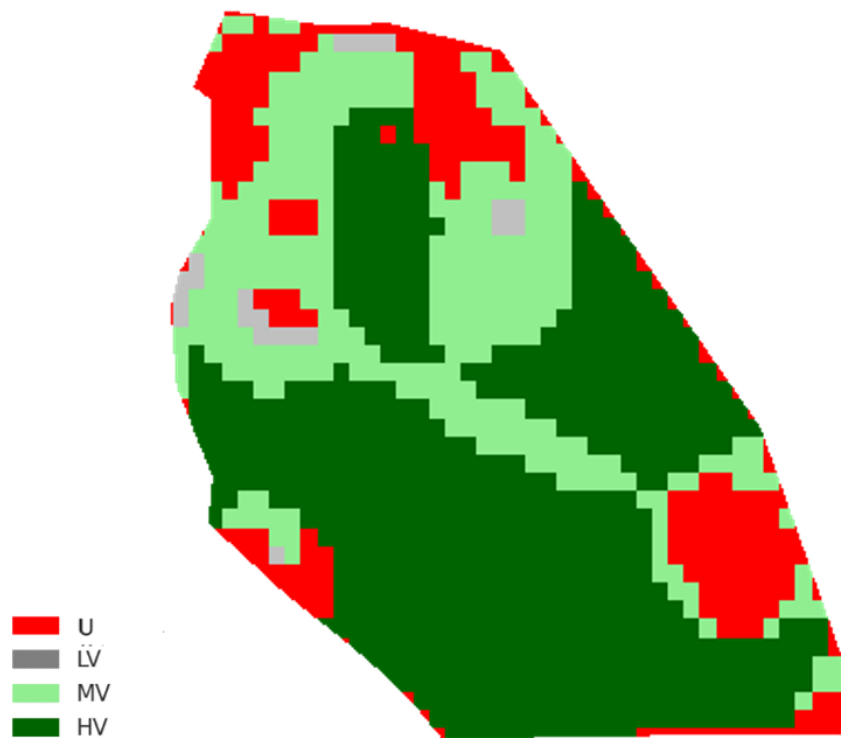


Fig. 2. Vigour stability map

Soil variability analysis

A sampling campaign was conducted to explain the variability found within the field, a. After identifying the macro areas, a UAV flight was carried out to confirm the vigor trends identified

from the historical data analysis and to precisely identify the most representative sampling points within the macro areas.

Soil Organic Carbon (SOC) and Soil Penetration Resistance (SPR) were measured at the identified points, and the results showed a trend in both SOC values and SPR values that varied according to the vigor level.

Figure 3a graphically represents soil penetration resistance (SPR) in megapascals (MPa) as a function of soil depth (cm) for three categories of vineyard areas: high vigor areas (HV), medium vigor areas (MV), and low vigor areas (LV). The colored lines represent different vigor levels: HV in purple, MV in green, and LV in blue. In general, SPR increases with depth for all vigor categories. LV areas show significative higher penetration resistance compared to MV and HV at all measured depths.

Agronomically, this can be explained by the fact that higher soil compaction indicates a reduction in soil porosity, limiting the movement and retention of water (Celik et al., 2010; Hamza and Anderson, 2005). Additionally, more compact soils restrict root growth, reducing the efficiency of plants in absorbing water and nutrients, which directly affects the plants' spectral response.

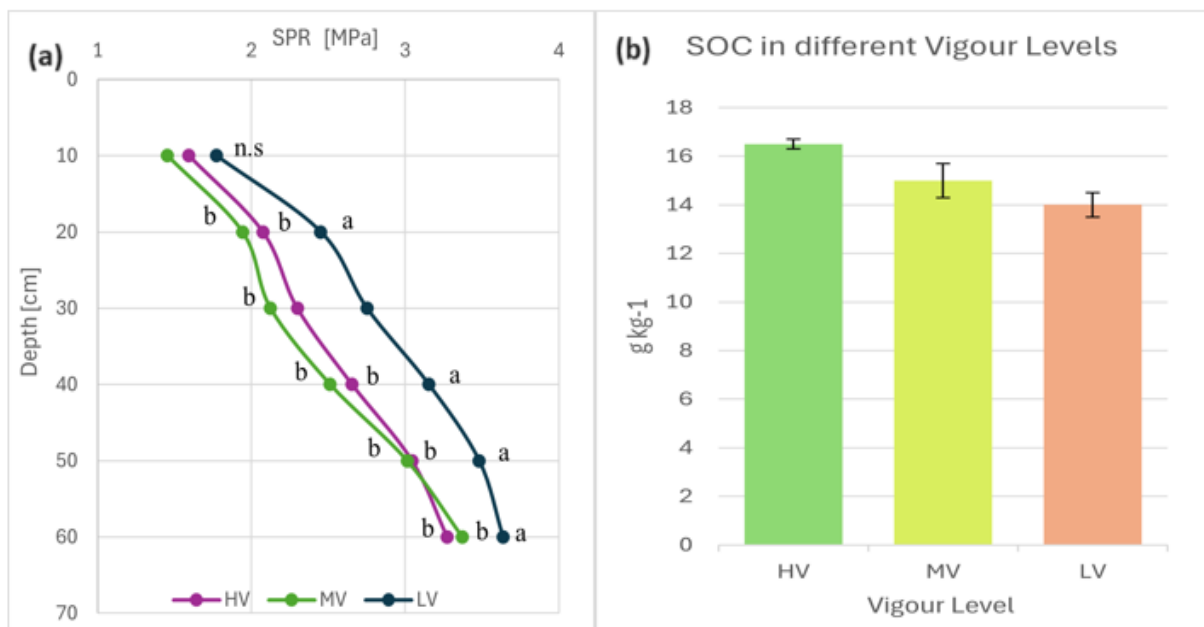


Fig. 3. Soil penetration resistance (SPR) in megapascals (MPa) as a function of soil depth (cm) (a) and Soil organic carbon (SOC) in grams per kilogram (g/kg) (b) for three vineyard area categories: high vigor areas (HV), medium vigor areas (MV), and low vigor areas (LV).

Figure 3b shows the soil organic carbon (SOC) content in grams per kilogram (g/kg) in relation to the different vigor levels of the vineyard: high vigor (HV), medium vigor (MV), and low vigor (LV). High vigor (HV) areas tend to have the highest SOC content, with a value close to 16 g/kg. Medium vigor (MV) areas show slightly lower SOC content, around 14 g/kg. Low vigor (LV) areas have the lowest SOC content, close to 13 g/kg. There is a clear positive relationship between the vigor level of vineyard areas and SOC content. Areas with higher vigor tend to have higher levels of soil organic carbon. Soil organic carbon is an important indicator of soil fertility, and higher SOC levels in HV areas could help explain their greater vegetative vigor (Blanco-Canqui and Benjamin, 2013). Overall, while SOC represents a key indicator for soil quality and vegetation, soil penetration resistance (SPR) provides crucial information on the physical structure of the soil and its implications for agricultural management.

Vineyard vigor prediction

The study of historical maps, together with UAV data collected at the end of winter (T1), enabled the generation of a predictive vigor map. This map was compared with the vigor map generated from the UAV monitoring conducted in the vineyard and the biometric survey campaign carried out in the vineyard.

The predictive map (Fig. 4a) was able to accurately predict 80% of the variability in the field. Specifically, class 1 (low vigor) was predicted accurately in 89.71% of cases, while in 10.29% of cases, it was predicted as class 2 (medium vigor). Class 3 (high vigor) was predicted accurately in 82.56% of cases, while in 17.44% of cases, it was confused with class 2. Class 2 was predicted accurately in 74.53% of cases.

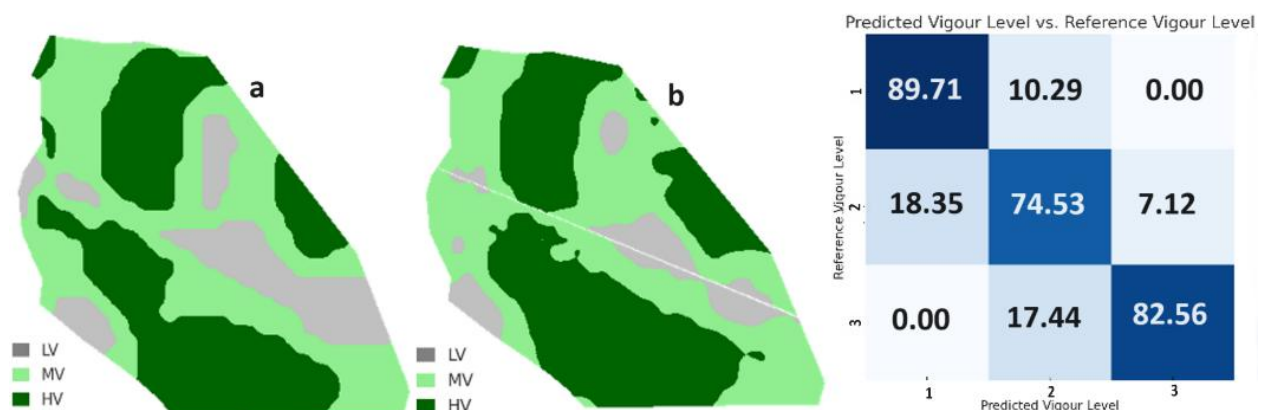


Fig. 4. Vineyard vigor maps: predictive vigor map (a) generated using historical and UAV winter data. The second image (b) shows the reference vigor map obtained from biometric surveys and UAV flights in the vineyard. The third image is a confusion matrix comparing predicted vigor levels with reference levels, showing an overall accuracy of 80%.

These results indicate a high level of precision for the predictive model, particularly for low and high vigor areas. However, the confusion between classes 1 and 2 and between classes 3 and 2 suggests room for improvement, especially in distinguishing medium vigor areas. Future improvements could include the use of more advanced algorithms or the integration of additional environmental and agronomic variables to further refine the predictions.

Conclusions

Soil conditions, such as penetration resistance and SOC, significantly influenced cover crop vigor and consequently overall vineyard growth. These characteristics remain stable in the short to medium term but, as confirmed by various studies, can vary in the medium to long term (Halvorson et al., 2002; Karlen et al., 1994). Additionally, the study enabled the identification of potential variability within the vineyard even before bud break. This allows for more precise soil management through early variable-rate fertilization, which can later be adjusted using spectral data related to the vineyard canopy. This approach can greatly benefit vineyard nutritional management by providing more time and preventing leaching and NO₂ emissions, which are more significant with frequent rainfall, a common occurrence in Mediterranean environments during winter and spring.

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Pruning weight estimation using multispectral sensors in a vineyard in southern Italy

Abstract

Precision viticulture demands characterization of the spatial variability of vineyard vegetative status to plan appropriate management. Pruning weight is an important indicator of vegetative growth and vine vigour. This study aims to provide a new approach for pruning weight estimation using multispectral sensors. The study was conducted in 2021 growing season, in a traditional Mediterranean vine-growing area in western Sicily (Camporeale, Italy). The methodology is based on analyzing multispectral images acquired using an Unmanned Aerial Vehicle (UAV) in a vineyard of Catarratto cultivar. Data acquired by multispectral surveys were got during the summer period. Pruning weight was measured in appropriate sampling points during the winter season. Using NRG (Near Infrared-Red-Green) imagery two vegetation indices were calculated, precisely Normalised Difference Vegetation Index (NDVI) and Green Normalized Difference Vegetation Index (GNDVI). Object-Based Image Analysis Approach (OBIA) was used with the purpose of canopy pixels segmentation from the soil and shadows. Correlation coefficients between vegetation indices and pruning weight were calculated. Pruning weight was estimated with a linear analysis model. NDVI showed high correlation with pruning weight providing good prediction results. This rapid and accurate methodology demonstrated high accuracy in vineyard pruning weight estimation, providing interesting potential to support grape growers to improve vineyard pruning management.

Keywords: Remote sensing; UAV; vegetation indices.

Introduction

Global wine consumption in 2022 was estimated to be approximately 232 million hectolitres. Although this consumption estimate has not changed significantly in recent years, it is still lower than in the pre-Covid era when it was around 242 million hectolitres. Along with the United States and France, Italy is one of the top wine-consuming countries in the world. Italy is also one of the main grapes producing countries, indeed, according to OIV data in 2022 production was 6.9 million tons, accounting for the second largest grape producer in the world after China (13 million tons). Globally, grape production in 2022 amounted to approximately 78.9 million tonnes, which decreased compared to previous years (OIV, 2023). Among the main factors that determined a worldwide decrease in production were unfavourable weather conditions (Catania et al., 2011). These results demonstrate the clear requirement to support and

improve the efficiency of wineries to successfully engage in an increasingly dynamic business sector. All this requires ongoing observation of the vine's agronomic parameters. One of the parameters that best describes the vineyard's vegetative status is the pruning weight. This allows the grapevine's growth, carbon storage cycle, vigour and reproductive balance to be assessed. The vegetative balance, i.e. the plant's potential to grow vegetative structures such as shoots and secondary shoots, is assessed by this parameter, which determines canopy density and thus indirectly measures potential yield (Taylor and Bates, 2012). Winter pruning is one of the main operations carried out in vineyards-to maintain the plants healthy and regulate the yield and grape quality. Furthermore, pruning is essential to maintain an optimal canopy architecture. Manually assessing the pruning weight is a time-consuming and labour-intensive process. Consequently, the introduction of automation in many vineyard operations is an increasingly desirable alternative. Furthermore, advanced proximal or remote sensing technologies have been widely applied in precision viticulture to survey various vegetative and reproductive parameters (Ferro and Catania, 2023b). Unmanned aerial vehicles equipped with a multispectral sensor can be used to extract vegetation indices (VI) that help farmers continuously to observe vineyard variability and stress conditions (Soubry et al., 2017). Furthermore, it is widely observed that there is a close relationship between the normalised difference vegetation index (NDVI) and vigour (Kasimati et al., 2023). In addition, the green normalised difference vegetation index (GNDVI) can provide information on the grapevine's health status by determining the vegetation's variability of its physiological parameters (Zúñiga Espinoza et al., 2017). The pruning weight based on multispectral drone imagery can be estimated by calculating relationships from infrared-based vegetation indices (J Baluja et al., 2012) or with regression models that combine vegetation reflectance with pruning mass.

The aim of this research was to estimate the vineyard's pruning weight using vegetation indices derived from multispectral images acquired by UAV with the purpose of generating a prediction map of pruning.

Materials and methods

Study Area

The study was conducted in 2021 in a 15-year-old vineyard with Catarratto cultivar, located in southern Italy in the province of Palermo (fig.1). The vineyard is located at an altitude of 315 metres above sea level. The surface area of the vineyard is 8.2 hectares. The plant density is

4170 vines per hectare and the rows are oriented north-east and south-west. The terrain is slightly hillside, with slopes of up to 18% at the steepest part. The vines are trained using the vertical shoot positioning (VSP) system and are pruned with a double spur cordon. Vineyard management follows standard agronomic practices, with shallow tillage (0.1 metre depth) during the growing season to limit spontaneous vegetation, water evaporation and prevent soil cracking.

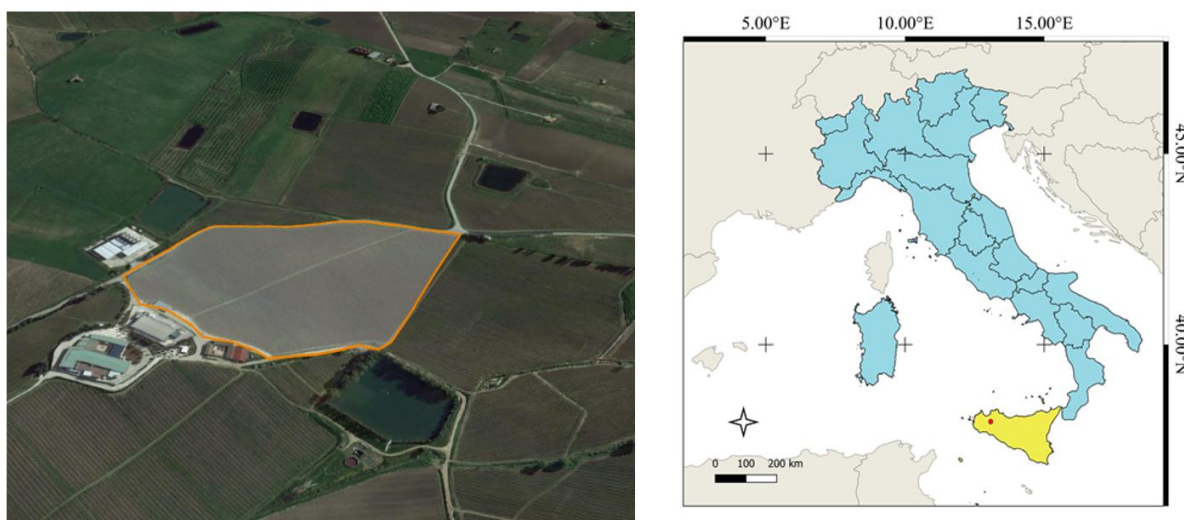


Fig. 1 Vineyard location in Sicily (southern Italy).

Experimental Procedure

Field data collection consisted of the identification and georeferencing of sampling plots and ground control points. Digital drone surveys were carried out and then the pruning weight parameter was assessed during pruning operations. The ground control points displayed in figure 2a with blue rectangular polygons evenly distributed throughout the sampling cells were georeferenced with a Stonex S70G GNSS receiver (STONEX® Srl, Milan, Italy), operating in RTK (real-time kinematics) mode and connected to the GNSS network.

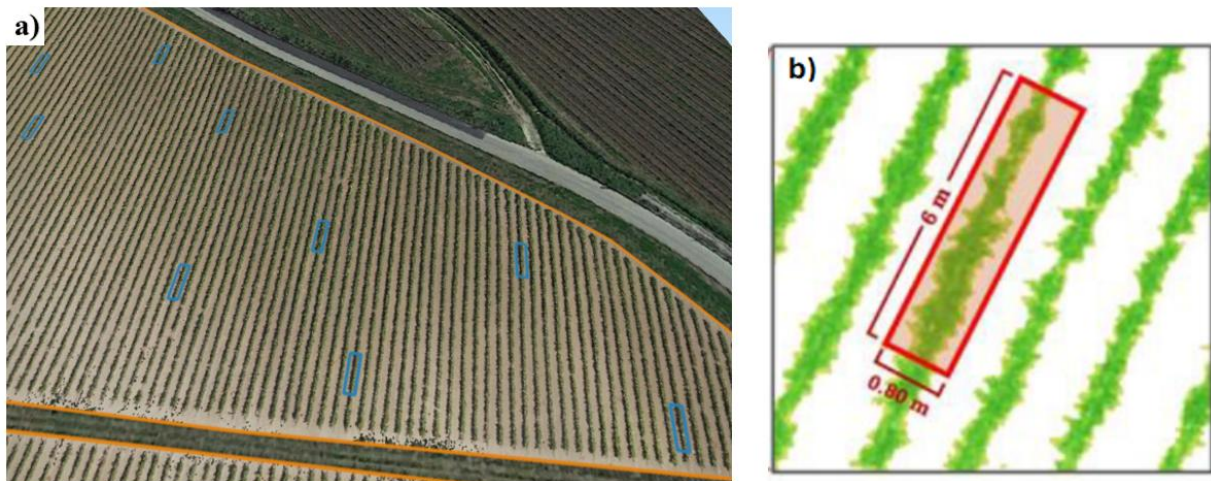


Fig. 2. Representative layout of the experimental design showing the replicates (blocks, represented in blue) in the vineyard (a); Illustration of a single sample block 6.00 x 0.80 m (in red) (b).

A total of 71 sampling blocks were considered. Each sampling block comprised 6 vines, therefore in each case the weight of 426 vines has been measured. The size of a sampling block was 6 metres in length and 0.80 metres in width (figure 2b). The coordinates of the ground control points were used to create the polygons in shape file format on a GIS analysis software.

The pruning residues were measured in the field at the end of the season with a calibrated balance.

Drone Imaging

The remote images were acquired with a Phantom 4 model from Da-Jiang Innovations (DJI), classified as a VTOL (Take-off and Landing Vertically-live). The Phantom 4 was used to acquire RGB and multispectral images and is equipped with a camera consisting of six 1/2.9" CMOS sensors.

The multispectral sensors are functional in the blue (B) bands: 450 nm, green (G): 560 nm, red (R): 650 nm, red-edge (RE): 730 nm, and near-infrared (NIR): 840 nm, with a resolution of 2.08 MP. Each sensor has a spectral sensitivity range of ± 16 nm relative to its nominal wavelength, except for the NIR-sensor, which has a spectral sensitivity range of ± 26 nm. A radiometric calibration was applied to the image sets, using reference images from a calibrated reflectance panel (LABSPHERE INC., North Sutton, US).

UAV flight sessions were conducted with a forward and lateral overlap of 60 % at a height of 70 metres above the ground from the take-off point, leading to an image pixel size (GSD) of 3.7 cm. The field of view (FOV) was 51.50 x 41.25 metres and the flight speed was 25 km/h. The camera captures images at intervals of 1 second, and the images were stored in TIFF format. During the 2021 growing season, three flight sessions were carried out at different grapevine phenological stages (table 1). The first flight (T1) was performed at day of the year (DOY) 167, while the second (T2) was performed at the beginning of ripening (DOY 200). The last flight (T3) was performed when the grapes were fully mature (DOY 241).

Table 1. UAV survey dates, days of the year, and growth stages.

Flight	DOY	Growth Stages
T1	167	berries pea size
T2	200	beginning of ripening
T3	241	full ripening

Flight operations were scheduled from 11:30 to 13:00. The georeferenced multispectral images were merged into a mosaic using Agisoft Metashape Professional Edition (Agisoft LLC St. Petersburg, Russia - <https://www.agisoft.com/>). A first post processing operation was to align the orthoimages. Afterwards, the dense point cloud and the multi-band orthomosaic were generated. Using QGIS version 3.23 software, it was possible to calculate the normalized difference vegetation index (Rouse Jr et al., 1974) and green normalized difference vegetation index. The NDVI was calculated using the NIR band and the red band. The GNDVI was calculated using the NIR band and the green band (Gitelson and Merzlyak, 1998). After processing the vegetation index maps, it was necessary to identify and segment the vineyard canopy from the soil and weeds by applying the unsupervised k-means segmentation algorithm as described by (Cinat et al., 2019).

Following an accurate field observation at different phenological periods, management areas with low (LV), medium (MV) and high (HV) vigour were identified, and then using GIS software, the vigour variability shown by the vegetation index rasters was assessed.

Statistical analysis

Vegetation index characteristics (count, mean, minimum, maximum and standard deviation) from the UAV raster images were extracted using the zonal statistics plugin in QGIS. The data obtained from the plant measurements were processed using an analysis of variance (ANOVA)

model. The significance level (α) was set at 99% ($p < 0.01$). Tukey's multiple comparison tests were used to identify the different averages. In addition, the relationships between vegetation indices and plant agronomic parameters were tested using regression analysis and Pearson's correlation coefficient (r). Simplified Linear Regression Model (SLRM) was applied using multispectral Vegetation Indices and pruning weight sampling data. The prediction model was developed based on a dataset of pruning weight sampling. All statistical procedures were performed using R software (R Core Team, 2022). Ordinary kriging interpolation was performed using the pruning weight prediction results obtained from the SLMR model based on vegetation indices. This method can express the spatial variation of a specific variable by minimising the error of spatial distribution of expected values. Kriging interpolation requires the estimation at an arbitrary location of a specific area of the field by linear weighting of all relevant observations.

Results and discussions

Analysis of the vegetation index rasters allowed the identification of three main vigour levels in both indices (fig. 3). These classes were derived using an unsupervised clustering approach, whereby the k-means algorithm partitioned the pixel values into three clusters, which were subsequently interpreted and assigned to low, medium, and high vigour levels based on their corresponding vegetation index mean values (Taylor et al., 2007). Based on these results, the plot consisted of 27% of the LV areas, which amounted to 2.23 ha when expressed in terms of area. The vineyard also consisted of a large MV area, representing 53% of the total, covering an area of approximately 4.36 ha. Finally, high vigour areas were identified which represented about 20%, which in terms of area is about 1.65 ha.

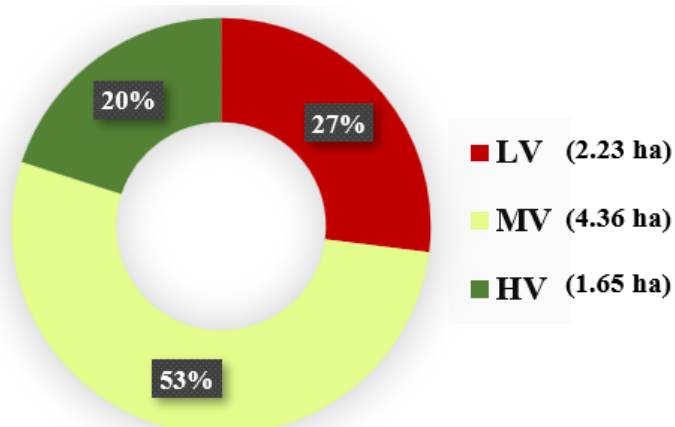


Fig. 3. Graphical representation of per cent vigor area distribution.

After quantifying the extent of the three vigor areas (LV; MV; HV), the statistics of the multispectral values of the two vegetation indices taken into consideration NDVI, and GNDVI were extracted. The mean values of the three vigor levels are shown in Table 2 and are relative to the survey during full vegetative activity of the plants (DOY, 200). The mean NDVI values of the LV vines were 0.60, which is different from that shown by the GNDVI index in the LV areas, which was 0.43. In the MV areas, the NDVI values were 0.65, while for the GNDVI index these values were 0.47. In the HV areas, on the other hand, the mean NDVI values were 0.71, which is significantly higher than the HV areas' value of the GNDVI index (0.53). For both indices, the highest standard deviation values were identified in the MV areas. The results suggest that the NDVI and GNDVI indices can be used to distinguish between grapevines with different vigor levels. The NDVI appears to be more sensitive to vigor level changes than the GNDVI. Additionally, the higher standard deviation values in the MV areas suggest that there is greater variability in vigor levels in these areas.

Table 2. Mean and standard deviation of VIs as a function of the three vigor levels.

	LV	MV	HV
NDVI	0.60±0.02	0.65±0.11	0.71±0.03
GNDVI	0.43±0.02	0.47±0.09	0.53±0.02

Based on the variability identified by the vigour indices, a similar principle was used to evaluate the pruning weight parameter. Indeed, table 3 shows the average values of plants pruning weight from the different sampling blocks of the entire field. The authors (Oldoni et al., 2020) using a similar approach identify through vegetation maps a high level of variability in vegetative vigour. Although the average shoot weight for the LV areas was about 0.30 kg, which was statistically different from the shoot weight of the MV and HV areas, which was 0.49 kg and 0.62 kg respectively. The standard deviation values identified further explain the variability distribution; within the MV cluster plants there is a high standard deviation, which is in line with the results previously reported concerning the vegetation indices. These results are in agreement with the findings of (Bonilla et al., 2013), in which a clear distinction in three vigour levels is evident.

Table 3. Distribution of vines pruning weight in the three vigor levels. S.D represent the standard deviation; the different letters denote statistically significant differences ($p \leq 0.01$).

Vigour level	Pruning weight (kg) $\pm$ S.D	
LV	0.30 $\pm$ 0.08	b
MV	0.49 $\pm$ 0.12	a
HV	0.62 $\pm$ 0.06	a

Table 4 presents correlation data between vegetation indices and pruning weight. It is observed that NDVI is a valid indicator for predicting pruning weight when evaluated at early phenological stages. These results suggest that remote observations should be carried out in the early stages of grapevine development for a more accurate estimation of pruning weight. In surveys conducted at late phenological stages, in conjunction with the senescence of chlorophyll tissues, there could be a risk of a less accurate assessment (Rey-Caramés et al., 2016).

Table 4. Pearson correlation coefficients between pruning weight and vegetation indices, with significance * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$, n.s = not significant.

	T1	T2	T3
NDVI	0.84***	0.77***	0.52 ^{n.s}
GNDVI	0.66**	0.70**	0.58*

The graphs in Figures 4a and 4b show the application results of the linear regression model for the prediction of pruning wood based on the NDVI (4a) and the GNDVI index (4b). In the first scenario, multispectral data recorded at T1 were considered, as NDVI was most correlated with pruning weight. The prediction model for this parameter provided an interesting result, in fact, the value of the determination coefficient was 0.69. A similar result was also obtained by (J Baluja et al., 2012), which confirm this relationship when the NDVI index is considered. In the second case, the linear regression model applied was based on the NDVI index data for the second survey period (T2). In this case, the results of applying the regression model were not satisfactory, in fact, a coefficient of determination of 0.51 was obtained.

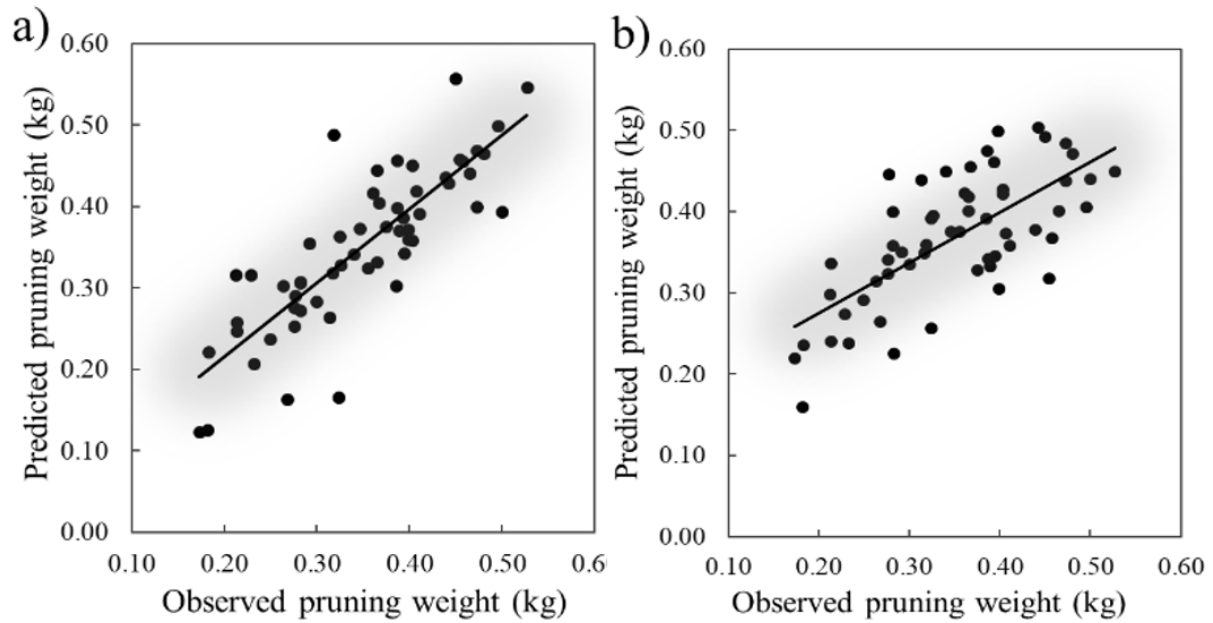


Fig. 4 Assessment of the linear correlation between predicted and observed pruning weight data. Prediction data obtained by applying the regression model on NDVI dataset fig (a); and GNDVI dataset fig (b).

Figure 5 shows a pruning map obtained from the linear prediction model developed with the NDVI data from the T1 survey. The prediction of the pruning weight map shows that in the LV areas with red colouring there is a pruning weight of approximately 0.30 kg, up to the HV areas with intense green colouring where pruning weight prediction values of close to 0.70 kg are reached. This result shows how one of the most important parameters of vine vigour, namely pruning weight, can be effectively estimated over large areas.

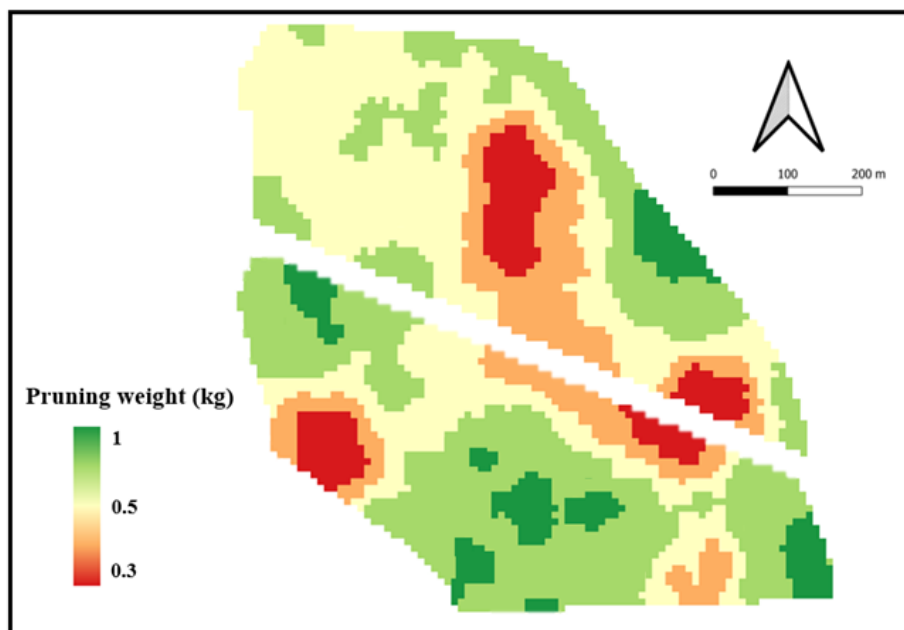


Fig. 5. Pruning weight prediction map obtained through kriging interpolation.

Conclusions

In conclusion, it can be stated that during the first two surveys carried out in the phenological phases of berries pea size and at beginning of ripening a significant correlation was observed between pruning weight and multispectral indices. Accordingly, it is appropriate to estimate the pruning weight of the vineyard before the onset of grape ripening. The interpolation method known as ordinary kriging was used successfully. In particular, it provided very accurate results when using vigour prediction data processed on the basis of NDVI. This suggests that the method used to estimate pruning weight is reliable and can be used with confidence in the context of vineyard management.

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Section 5. Development of prescription maps for precision agriculture

Developing high-resolution nitrogen prescription maps using UAV-based multispectral data and dilution curve approach

Abstract

Effective nitrogen (N) management is essential for maximizing potato yields while promoting sustainable farming practices. The Nitrogen Nutrition Index (NNI), a widely recognized indicator of plant N status, plays a crucial role in optimizing fertilization strategies. Conventional methods estimate NNI through destructive field-based measurements, but advancements in remote sensing (RS) now offer a more efficient and comprehensive way to assess crop N variability across agricultural fields.

This study leverages multispectral data acquired via Unmanned Aerial Vehicle (UAV) and machine learning (ML) models to predict potato NNI and generate prescription maps for site-specific N fertilization. The UAV-captured multispectral imagery was processed to extract spectral bands and a wide range of vegetation indices, with a feature selection algorithm identifying the most relevant predictors to enhance model performance. These selected features were then used to train and evaluate multiple ML models. The framework used provided accurate NNI predictions comparable to ground-based estimates. Using these predictions, the nitrogen requirement (NR) of the plants was calculated, allowing the generation of prescription maps for optimized fertilization. This integration of UAV multispectral data and ML effectively captured spatial variations in crop N status over time, enabling a targeted approach to nitrogen application and consenting to improving the efficiency of N fertilization.

Overall, this approach offers a robust framework for precision N management, supporting data-driven decision-making for optimizing fertilization and enhancing resource efficiency in potato production.

Keywords: Precision Agriculture, UAV, Nitrogen Use Efficiency, Machine Learning, Nitrogen Nutrition Index.

Introduction

Nitrogen (N) fertilization is one of the most critical yet challenging management practices in agriculture, as it must be carefully regulated in space and time to ensure crop productivity while mitigating environmental risks. In potato production, optimized N management can substantially increase yields while reducing N losses through leaching and gaseous emissions, which are major contributors to environmental degradation (Kempenaar et al., 2017). Consequently, agronomic research has devoted significant efforts to developing novel approaches and tools aimed at improving N use efficiency (NUE) and sustainability (Goffart et al., 2023).

A cornerstone of these efforts is the N Nutrition Index (NNI), which provides a quantitative assessment of crop N status. Defined as the ratio between the actual plant N concentration and the critical N concentration (N_c) derived from the critical N dilution curve (CNDC), the NNI offers an integrative indicator of plant N sufficiency. Values close to one indicate optimal N nutrition, values below one signal N deficiency, and values above one reflects luxury consumption. As such, the NNI has been widely used across herbaceous crops not only as a diagnostic tool but also as a proxy for other key parameters, including NUE, radiation use efficiency, and ultimately yield potential (Hu et al., 2014). Most importantly, the NNI serves as a direct proxy for the N requirement (NR) of the crop, making it the fundamental parameter for translating plant status into actionable fertilization strategies (Peng et al., 2021). By mapping NR at the field scale, prescription maps can be derived for site-specific N applications, with the resolution tailored to the operational capacity of the machinery. This positions NR as the operational link between crop monitoring and precision N management.

Traditionally, NR measures rely on destructive sampling of plant tissues to quantify biomass and N concentration. While accurate, such methods are time-consuming, labor-intensive, and inherently limited in both spatial coverage and temporal resolution. These constraints hinder their practical application in modern precision agriculture, where high-frequency and spatially explicit monitoring is required (Carella et al., 2024; Roma et al., 2025b).

To overcome the limitations of destructive sampling, non-destructive methods have been developed to estimate NNI and NR directly from crop spectral characteristics (Canicattì and Vallone, 2024). Spectral bands in the green, red-edge, and near-infrared regions, as well as vegetation indices derived from them, have been shown to be sensitive to canopy N status.

Recent advances in remote sensing (RS) have further accelerated this field, with Unmanned Aerial Vehicles (UAVs) offering high spatial and temporal resolution imagery that surpasses traditional satellite platforms. Coupled with machine learning (ML) algorithms, UAV-based multispectral data have enabled accurate and timely estimation of crop N status in several crops (Jiang et al., 2023; Qiu et al., 2021). However, despite the agronomic importance of potato cultivation, applications of UAV and ML approaches to NR estimation in potato systems remain scarce.

This gap underscores the need for robust frameworks that integrate advanced CNDC modeling with UAV-based spectral monitoring and ML analytics. Such integration holds the potential to provide reliable NR estimation, derive spatially explicit NR maps, and ultimately enable precision fertilization in potato cropping systems.

Materials and methods

Experimental site and Data acquisition

Field experiments were conducted over two consecutive growing seasons (2018–2019) in Central Denmark at the Department of Agroecology, Aarhus University, Viborg (56° 31' 41" N, 9° 24' 53" E; WGS 84, EPSG: 4326).

The crop cultivated was potato (*Solanum tuberosum* L.), variety Oleva, transplanted in early May with 0.85 m row spacing and 0.35 m plant spacing.

Each year, N response plots were established to investigate the N dilution mechanism and to define NUE. These trials followed a randomized block split-plot design with two replications and included 10 plots per year. Treatments consisted of five N application rates (0, 60, 140, 200, and 260 kg N/ha). All plots were fully irrigated throughout the growing season to avoid water stress and ensure that crop responses reflected N availability.

In addition, adjacent fields were used for experimentation, covering 2.61 ha in 2018, and 2.58 ha in 2019. Experimental plots measured 24 × 24 m and were arranged in a randomized block design with a split-plot treatment structure replicated four times.

Fertilization management consisted of two levels: a full dose (N2), consistent with Danish agricultural guidelines, and an optimized dose (N1), applied in split applications following the approach of Zhou et al. [9]. Mid-season sampling of plants and tubers was carried out each year,

in correspondence with the phenological stage of tuber formation stage. All samples were stored at 4 °C, weighed fresh, and then oven-dried at 60 °C for 48 h to determine dry matter (DM). Dried material was ground and analyzed for N concentration (%N) using the Dumas combustion method (Elementar Analysensysteme GmbH, Germany). Multispectral data were acquired under stable illumination between 10:00 and 14:00. A DJI Matrice 100 quadcopter (DJI, China) carrying a Micasense RedEdge multispectral camera (Micasense, Seattle, USA) was employed, acquiring blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and NIR (840 nm) bands. Flight altitude was 70m with a speed of 4.5 m/s, yielding a ground sampling distance (GSD) of 0.05 m/pixel. Georeferencing was ensured using four to six ground control points (GCPs) positioned at field boundaries and recorded with a Trimble RTK GPS (Trimble Inc., USA), while radiometric calibration was performed with reference panels scanned before and after each flight.

Multispectral images were processed using Pix4Dmapper (version 4.2.27, Pix4D SA) to generate orthorectified mosaics and 3D point clouds. The resulting products were refined in QGIS (QGIS Development Team, 2023) and Python (Python Software Foundation, 2023). For each sampling date, mean reflectance values of spectral bands were extracted using the *zonal_stats* function of the *rasterstats* Python library. In addition, a wide set of vegetation indices (VIs) was calculated based on the available bands and literature evidence.

Determination of Nitrogen Nutrition Index and Nitrogen Requirement

To reliably determine the NNI, we adopted the partially-pooled Bayesian hierarchical framework introduced by Canicatti et al. (Canicatti et al., 2025). This method enables robust estimation of the parameters of the critical N dilution curve (CNDC) while explicitly accounting for variation across locations, cultivars, and management practices. A comprehensive dataset was assembled by integrating data collected globally with additional experimental data from the presented study.

The NNI was subsequently computed as the ratio between the measured plant N concentration (%Na) and the critical N concentration (%Nc) estimated from the CNDC. A detailed description of the modelling framework, prior specification, and diagnostics is provided in Canicatti et al. (Canicatti et al., 2025).

NR was calculated as the difference between the N given to place where NNI was lower than to reach the level that plant had NNI=1, this one was corrected for the capacity of the plant to absorb the N, the NUE.

Then a recommended N supply during the season was evaluated based on the recommendation, then if NNI Was higher than 1 no fertilization (or reduced), if is 1 I give the recommended, if is lower I give more than the recommended.

NR was derived as:

$$NR = \mu * \frac{\left(\frac{PNU}{NNI}\right) - PNU}{NUE} \quad (1)$$

where PNU is the plant N uptake (kg N ha⁻¹), NNI previously calculated, NUE estimated from fertilizer response trials, which value was 0.65 and μ is a deficiency threshold set at 1 (Cilia et al., 2014; Giletto and Echeverría, 2012; Peng et al., 2021). According to this formulation, positive NR values indicate the amount of N required to correct an in-season deficiency, while negative values suggest a surplus of N already present in the system. This method integrates physiological information from the critical N dilution curve with agronomic efficiency parameters, providing a robust tool to guide N fertilization strategies under field conditions.

UAV-based Nitrogen Requirement prediction

The NR values derived from previously discussed section were used as targets to train a UAV based ML algorithm, with multispectral bands and vegetation indices serving as predictors. The complete dataset included 22 variables, which were reduced to 14 through ReliefF feature selection in Regression Learner App in MATLAB (Robnik-Šikonja and Kononenko, 2003, 2024). Data were randomly split into training (90%) and testing (10%) sets, and a 5-fold cross-validation was applied to reduce overfitting risk. Several regression models were tested in MATLAB and Gaussian process regression (GPR) was chosen as obtained the best performance. Model performance was evaluated using multiple error metrics, with coefficient of determination (R²), root mean square error (RMSE), mean squared error (MSE), and mean absolute error (MAE) selected as the main indicators.

Nitrogen Requirement and fertilization maps creation

The best-performing model was applied to UAV imagery to generate spatially explicit NNI maps. A Python–MATLAB workflow was implemented, where TIFF-format images were transformed into arrays, processed through MATLAB for prediction, and re-exported to raster format.

Results and discussions

Machine learning algorithm for NR prediction

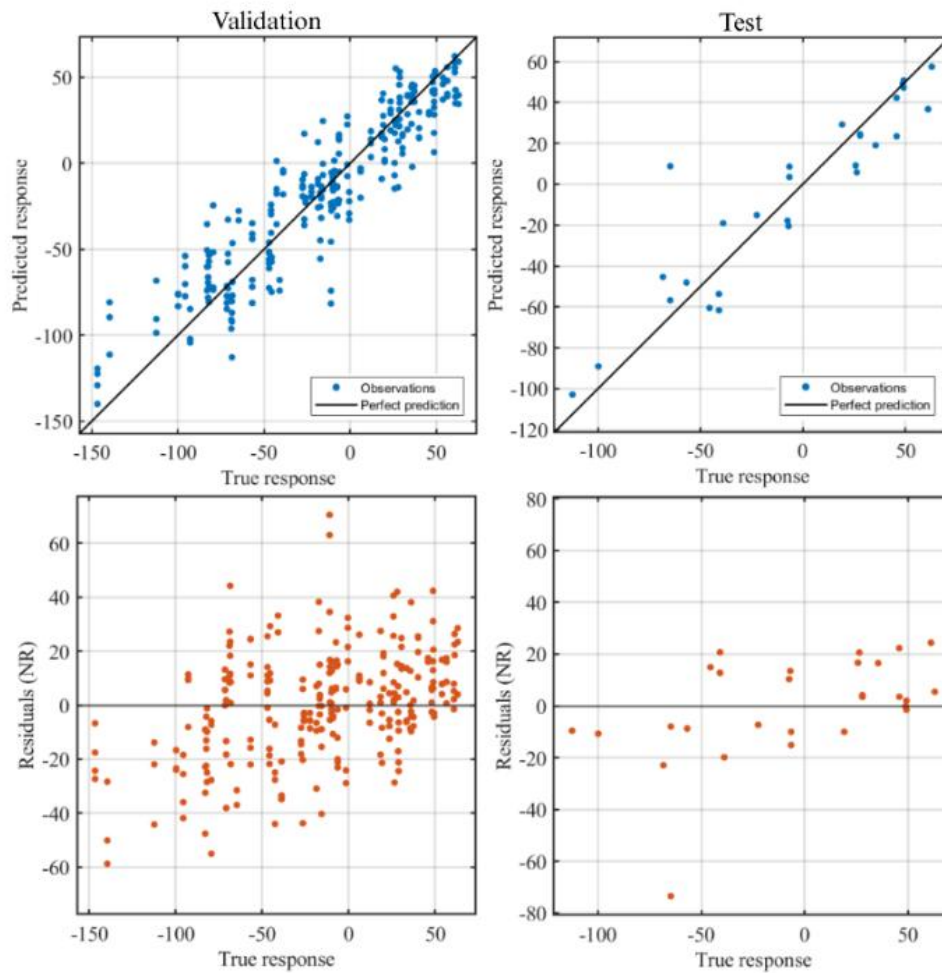


Fig. 1. Performance of GPR model for predicting NR in the validation (left) and test (right) datasets. Top panels show the relationship between observed and predicted responses. Bottom panels display residual plots.

The GPR model demonstrated satisfactory performance in predicting NR across both the validation and test datasets (R^2 respectively of 0.85 for both) indicating that the model

effectively captured the variability of NR across the observed range. Residual analysis revealed that most deviations were contained within ± 20 units, with no evident systematic bias across the response domain, although a tendency toward underestimation was observed at higher NR values.

Performance in the test dataset confirmed the robustness of the model. Predicted responses aligned well with the true values, particularly within the central range of NR, with limited scatter and reduced error magnitudes compared with the validation set. Residuals were symmetrically distributed around zero, suggesting the absence of heteroscedasticity and supporting the generalization capability of the model. The overall results highlight the ability of the GPR approach to provide reliable NR estimates, these findings are consistent with previous studies where GPR has proven effective in handling non-linear relationships and limited sample sizes in agronomic applications (Xu et al., 2023; Zhang et al., 2024). Compared with linear or tree-based approaches, which often struggle to account for complex response dynamics or tend to overfit under sparse conditions, the GPR framework demonstrates superior flexibility and reliability (Liu et al., 2023).

Nitrogen Requirement and Nitrogen prescription maps

The NR maps (Fig.2 and Fig.3) generated in this study provided robust and quantitative insights into crop N demand at high spatial resolution. These maps revealed not only the overall N status of the crop but also highlighted marked spatial variability within fields. Remarkably, such variability was observed even in plots that had received the same fertilization inputs and were characterized by comparable soil N availability. Differences also emerged among replicates, reinforcing the notion that factors beyond fertilization rates and baseline soil conditions influence crop N uptake and utilization (Chiriac et al., 2025). This spatial heterogeneity underscores the complexity of plant–soil–environment interactions and reveals the intrinsic variability of crop N status (Canicatti et al., 2025).

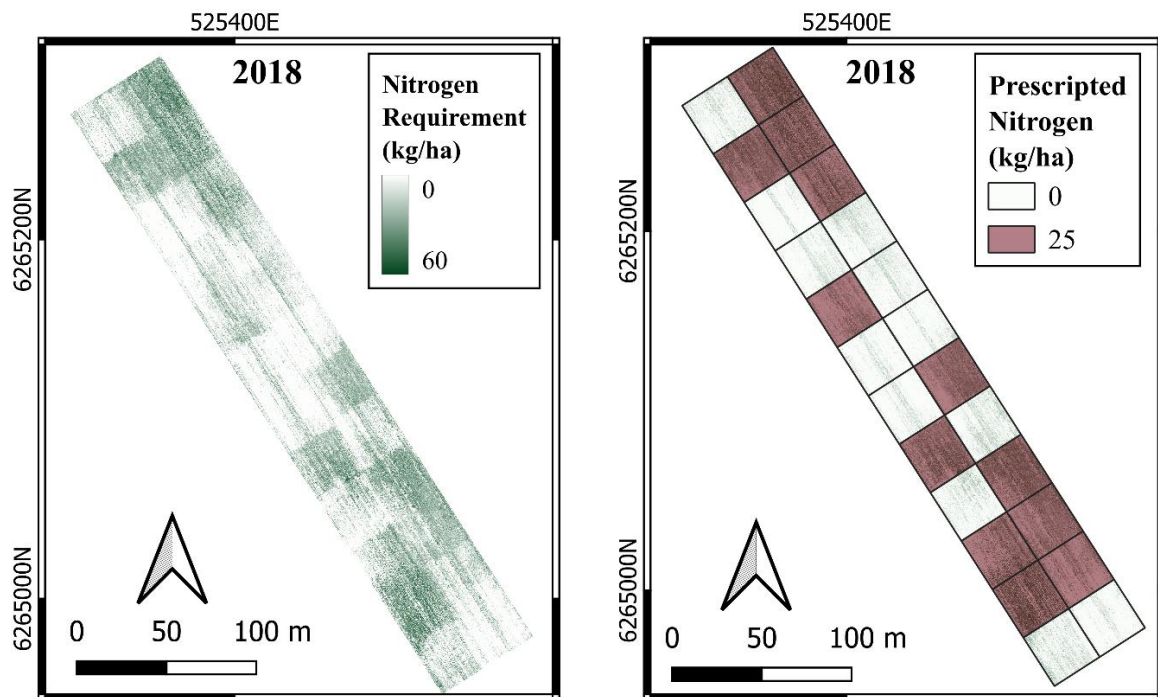


Fig. 2. High-resolution NR maps (EPSG:32632 -WGS84/UTM Zone 32N) for the 2018 growing season (left), expressed in a green scale ranging from 0 to 60 kg N ha⁻¹, and the corresponding prescription map (right), aggregated at a plot resolution of 24 × 24 m (0 and 25 kg N ha⁻¹) for variable-rate fertilization purposes.

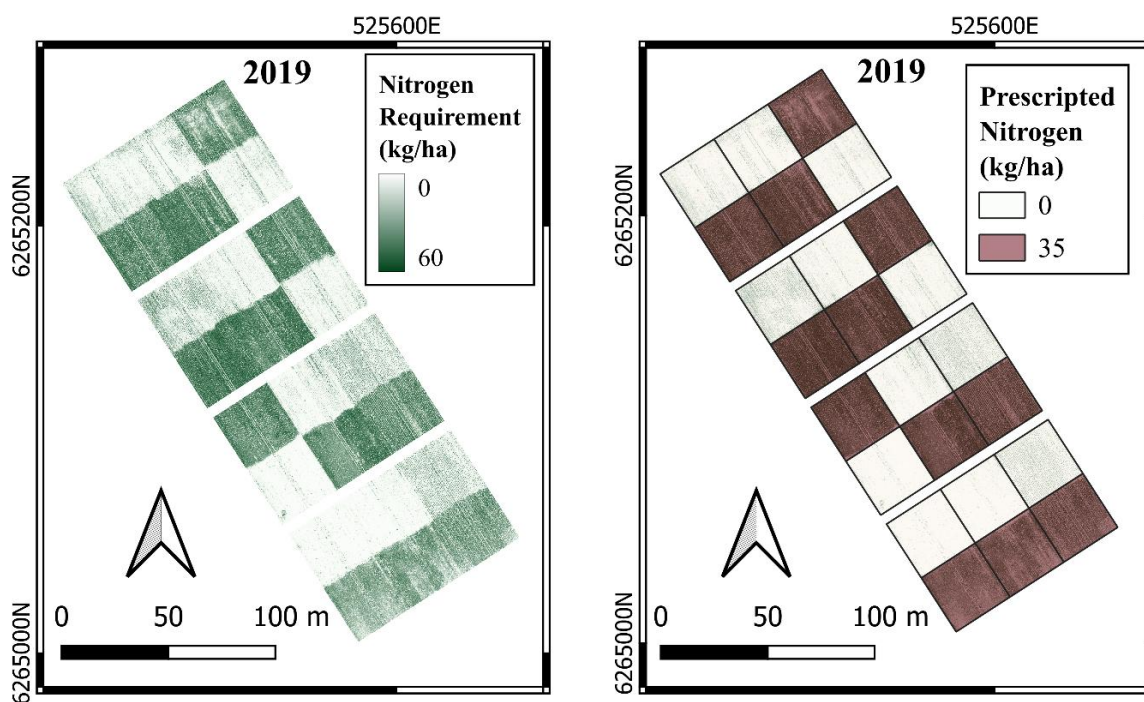


Fig. 3. High-resolution NR map (EPSG:32632 -WGS84/UTM Zone 32N) for the 2019 growing season (left), expressed in a green scale ranging from 0 to 60 kg N ha⁻¹, and the corresponding prescription map (right), aggregated at a plot resolution of 24 × 24 m (0 and 35 kg N ha⁻¹) for variable-rate fertilization purposes.

By providing spatially explicit information, NR maps constitute a direct bridge to prescription fertilization. In practice, these maps can be translated into actionable fertilization strategies tailored to the variability within fields. The resolution of the prescription maps can be adapted to the operational capabilities of agricultural machinery, making them highly relevant for farmers seeking to apply N site-specifically (Lu et al., 2022; Roma et al., 2025a). However, when translating NR estimates into operational recommendations, it is important to recognise the uncertainty associated with future crop growth and soil N mineralization, both of which may deviate from expectations due to weather and management interactions. Because underestimating N supply carries a higher agronomic and economic risk than modest overapplication, the use of a practical buffer or safety margin (+10/15%) is often warranted to support robust decision-making under variable field conditions. Beyond the clear economic benefit of optimizing input use, this approach contributes to broader sustainability goals by reducing nutrient losses and minimizing environmental impacts.

Conclusions

The integration of Bayesian modeling, ML algorithms and remote sensing created a framework that not only enhanced the agronomic efficiency of fertilization but also supported the transition towards environmentally sustainable agriculture.

These findings are particularly relevant as they open new perspectives for precision N management. The detection of intra-plot variability in NR suggests that crop responses are shaped by multiple factors, including micro-variations in soil properties, root distribution, water availability, and genotype-specific physiological traits. Investigating these drivers will be key to better understanding the mechanisms governing NUE and the capacity of crops to acquire and assimilate N. Such knowledge is fundamental not only for yield optimization but also for addressing critical environmental processes, such as nitrate leaching and nitrous oxide emissions, which are directly linked to excessive or inefficient N use.

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Fertilisation prescription map in olive orchard using UAV multispectral camera

Abstract

The applications of Precision Oliviculture (PO) increased in recent years to improve the quality and quantity of extra virgin olive oil. In intensive cultivation systems, several cultural practices such as fertilisation enable the plants' vigour to be balanced and maintained, reducing the management costs. The aim of the study compared the fertilisation saving obtain among standard fertilization and two different prescription maps obtained from two methodologies, applicable through a geographic information system (GIS), in an olive orchard. The experiment was carried in an intensive olive orchard located in western Sicily (Italy). Multispectral images were acquired using a remote platform. Specifically, the Phantom4 (Unmanned Aerial Vehicle, UAV) was used in automatic flight configuration at an altitude of 70 m a.g.l.. QGIS ver 3.28 software was used to carry out segmentation and classification of the Digital Elevation Model (DEM) and the orthomosaic extracted from the photogrammetric process. The Object-Based Image Analysis (OBIA) process made it possible to extract canopy area (CA), and spectral condition such as NIR, Red and NDVI (Normalized different vegetation index) for each plant. First prescription map was developed to identify the are-as requiring nitrogen fertilization using the information extracted from the multispectral images. The second prescription map, created within the previously identified area, performing a nitrogen nutritional balance per plant taking into account soil variability and vigor conditions. Study showed that the technology used and image analysis processing were able to estimate the vigor conditions and may represent a

valuable solution to investigate spatial variability and sustainable management of cultivation practices, obtaining a fertilisation saving between the 24% to 33%.

Keywords: OBIA, Precision Oliviculture, remote sensing.

Introduction

The continuous evolution of olive cultivation techniques worldwide makes it necessary to increase production efficiency to maximise economic and environmental sustainability, through improved agronomic techniques (FAOSTAT, n.d.). This aim can be pursued through principles of precision agriculture, since using new technologies it is possible to monitor and assess the growing conditions of plants, in order to manage them in a spatially variable manner (Becce et al., 2024; Pagliai et al., 2021).

The applications of precision oliviculture (PO) begin with the identification and characterisation of the spatial and temporal variability present within olive orchards in different agro-ecosystems (López-Granados et al., 2004; Roma and Catania, 2022). This variability can be found at pedological (Gargouri et al., 2006), environmental and crop (López-Granados et al., 2004; Rubio-Delgado et al., 2021) scales of detail. In the last decade, research on PO has mainly focused on the identification and evaluation of field variability (Sarri et al., 2020) and the consequent variable rate distribution (VRA) of different production factors such as water, pesticides and fertilisers (Pagliai et al., 2022). For many years, the over-fertilisation of olive orchards has been a common practice, often carried out without considering spatial variability, leading to economic, qualitative and environmental consequences that are not in line with the new production objectives. Many studies highlight that there is not always a need for massive annual fertiliser doses, as they can lead to a reduction in polyphenols and unbalance vegetative-productive activity (Fernández-Escobar et al., 2006). Precision fertilisation is an essential practice in olive cultivation that can lead to dose savings of around 30% (Roma et al., 2023c; Van Evert et al., 2017).

To apply variable rate fertilisation, the farmer must necessarily be able to load a prescription map into a 4.0 machine. Prescription maps allow the variable rate distribution of fertilisers and are created from the base maps of available information sources (Campos et al., 2020). In general, base maps are able to show the spatio-temporal variability of the main factors influencing the physiological and growth conditions of plants. Among these, the most widely

used are production maps, leaf nutrient concentration maps (López-Granados et al., 2004; Rubio-Delgado et al., 2021), soil maps (Gargouri et al., 2006), vigour maps and multi- and hyper-spectral maps (Aggelopoulou et al., 2011; Álamo et al., 2012; Roma et al., 2023c). Soil base maps can be assessed by taking different numbers of soil samples that allow for an accurate description of variability or be by geo-resistivimeters and/or georadar (Aggelopoulou et al., 2011; Gargouri et al., 2006). Vigour maps are increasingly obtained by processing multispectral images acquired from remote acquisition platforms such as Unmanned Aerial Vehicles (UAVs).

The aim of the study was to propose two different methodologies applicable via a geographic information system (GIS), to create a nitrogen fertiliser prescription map in the olive orchard that takes into account the real soil and cultivation conditions of the agro-ecosystem. Specifically, a first prescription map was created to identify the area that really needed nitrogen fertilisation in which a standard dose of fertiliser could be applied. On the other hand, the second prescription map was created within the previous area in order to identify homogeneous management areas that took into account the real nutritional needs and plant health conditions. The proposed experiment permits to quantify the nitrogen fertiliser savings (kg/ha) obtained through the two prescription maps compared to a standard dose set at 100 kg/ha.

Materials and methods

Experimental site

The study area is located in Segesta (Trapani, southern Italy) on a flat plot of 5,800 m². According to the Koppen-Geiger classification, the area falls in a Mediterranean zone, while the soil moisture regime is xeric tending to arid (Kottek et al., 2006). The study was carried out during the 2022 season in an olive orchard (*Olea europaea* L., cv. Cerasuola) cultivated with an intensive 5×5.5 m training system, managed with ordinary practices without the use of irrigation.

Ground survey

Field sampling was carried out in order to investigate soil and crop variability. In both cases, a regular sampling grid was applied excluding the outermost part of the field. Soil samples were taken at each grid intersection point at a depth of 10 to 30 cm on DOY 51. Leaf sampling was

performed taking 50 leaves per plant of different vigour, located near the sampling nodes on DOY 93; following the methodology used in other studies (Fernández-Escobar et al., 2009; López-Granados et al., 2004; Roma et al., 2023c). Soil samples were analysed to determine texture, electrical conductivity (EC), organic matter (OM) and total nitrogen concentration (Soil nitrogen, SN). Leaf samples were analysed to determine the total nitrogen content (Leaves nitrogen, LN).

UAV survey

Multispectral images were acquired using a Phantom4 Multispectral (DJI Ltd., Shenzhen, China) equipped with a multispectral camera with one RGB and five monochrome 2.08 MP sensors (Blue, Green, Red, RedEdge and Near Infrared), a field of view (FoV) of 62.7° and a focal length of 5.74 mm. The image overlap ratio was 70%. The flight was performed in automatic mode using determined waypoints using RTK (real time kinematic) differential correction at an altitude of 70 m, generating imagery with spatial resolution of 3.6 cm. The flight was carried out on DOY 93 simultaneously with the leaf sampling at midday in best weather condition. Before the flight, five ground control points (GCPs) and a calibration panel were placed prior to the flight to perform the geometric and radiometric corrections, respectively. Photogrammetric reconstruction was performed using Agisoft Photoscan Professional software (version 1.7.3., St. Petersburg, Russia), and geospatial data analysis and processing using QGIS software ver. 3.28. Using the GIS software was performed the segmentation and classification to obtain the canopy area (CA) and NDVI for each plant (Ferro et al., 2024b).

Prescription maps creation

Two different prescription maps were created for the experiment. First, spectral and biometric information were extrapolated for each plant. Next, the behaviour of NDVI (Normalized Difference Vegetation Index, (Jhon W Rouse et al., 1974)), NIR, Red and CA were analyzed to determine the best predictor of LN. Finally, the prescription maps were generated. The first prescription map was focused on the identification of the area requiring nitrogen fertilization observing the spectral behaviour on Red bands versus LN data for all sample plants. Next, the regression model was determined and the LN levels of all plants were estimated according to their spectral conditions. The continuous LN map was obtained by geostatistical spatialisation

of the results obtained from the regression model (Base Map1). Finally, the prescription map1 was obtained by thresholding the base map1 using the minimum foliar nitrogen concentration threshold of 1.2%, as reported in the literature (Fernández-Escobar et al., 2009). This threshold represents the nitrogen concentration limit that differentiates plants in good nutritional condition from deficient varieties.

The second prescription map was created using the area identified in the previous prescription map, performing a nitrogen nutritional balance per plant taking into account soil variability (Akdemir et al., 2018) and vigour conditions (Fernández-Escobar et al., 2012; Maran and Fernandez-Escobar, 1996; Rodrigues et al., 2012). Crop variability was used to identify sub-plots with different vigour. For this purpose, canopy area, canopy volume and NDVI were used and were identified: low (LV), medium-low (M-LV), medium-high (M-HV), high (HV) classes. The nutritional balance was carried out considering the amount of nitrogen removed by production and pruning in previous year (Akdemir et al., 2018; Roma et al., 2024b) and nitrogen use efficiency (NUE established at 45.9% according (Maran and Fernandez-Escobar, 1996)). Soil variability was taken into account to quantify the amount of nitrogen available, using the soil maps created.

Results and discussions

The experimentation carried out allowed the quantification of the hypothetical savings that can be obtained by carrying out a variable rate distribution of nitrogenous fertilisers in olive cultivation, using different methods for the creation of prescription maps. OM and SN had a content of less than 1%, probably due to the high mineralisation that generally occurs in Mediterranean environments. However, they played a key role in determining soil fertility and plant growth (Perna et al., 2022). Indeed, OM (Figure 1), SN and sand content were positively correlated at high significance levels ($pvalue < 0.05$) with plant vegetative characteristics. Gálvez et al., (2004) (Gálvez et al., 2004) also reported that increased percentages of silt and clay in the soil are correlated with reductions in the vigour level of olive plants. In the central area of the plot, a condition of low fertility was observed, as shown by the organic matter base map (Figure 1).

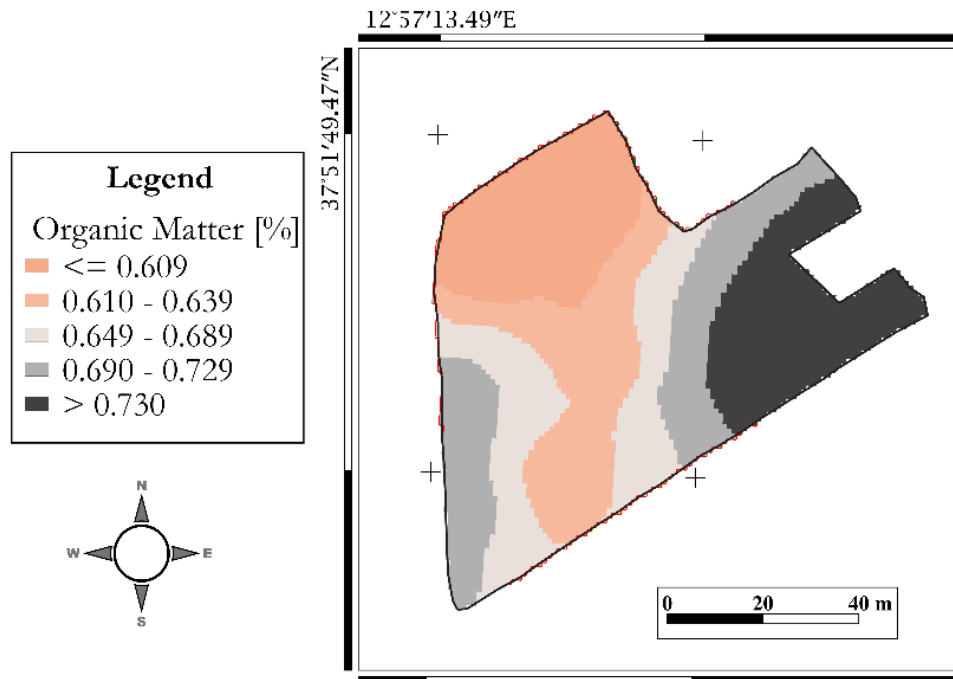


Fig. 1. Organic matter map obtained by spatialisation using a geostatistical model of soil samples.

The foliar nitrogen concentration map was also lower in the central part of the plot and higher in the outer areas. The congruence between the OM map and LN suggests that these two parameters are strongly correlated and influenced.

When observing the correlation between LN and the spectral reflectance data of the entire canopy, opposite trends were observed. The reflectance in the Red band was positively correlated via a second-degree polynomial model and statistically significant, while the reflectance in the NIR band was not correlated with the LN of the leaves (Figure 2). The behaviour of the NIR band was different to that observed in other studies (Rubio-Delgado et al., 2021; Yoder and Pettigrew-Crosby, 1995). However, studies combining LN with spectral response are carried out using hyperspectral sensors chambers and on a sample of leaves only. In the experiment, the response of the entire canopy was considered instead, which seemed to be most influenced by the vigour and development conditions of the CA (Catania et al., 2022). This assumption would confirm the low correlation observed between NDVI and leaf LN.

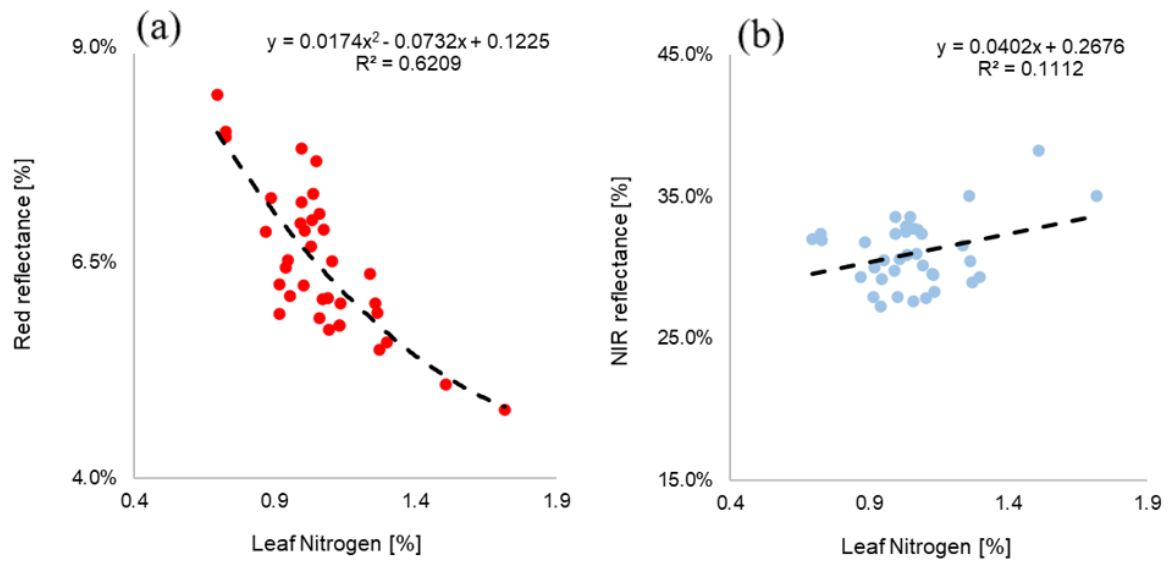


Fig. 2. Linear regression between (a) red-band reflectance (650 ± 16 nm) and (b) NIR reflectance (840 ± 26 nm) with leaf nitrogen (LN) content.

Using the regression line between red reflectance and foliar LN, the nutrient conditions of all plants were estimated and the prescription map1 was created (Figure 3a). As can be easily observed, the area that really needs nitrogen fertilisation in order not to cause a vegetative-productive unbalance was 76%. Furthermore, a correspondence can be observed between the OS map and the prescription map obtained by thresholding.

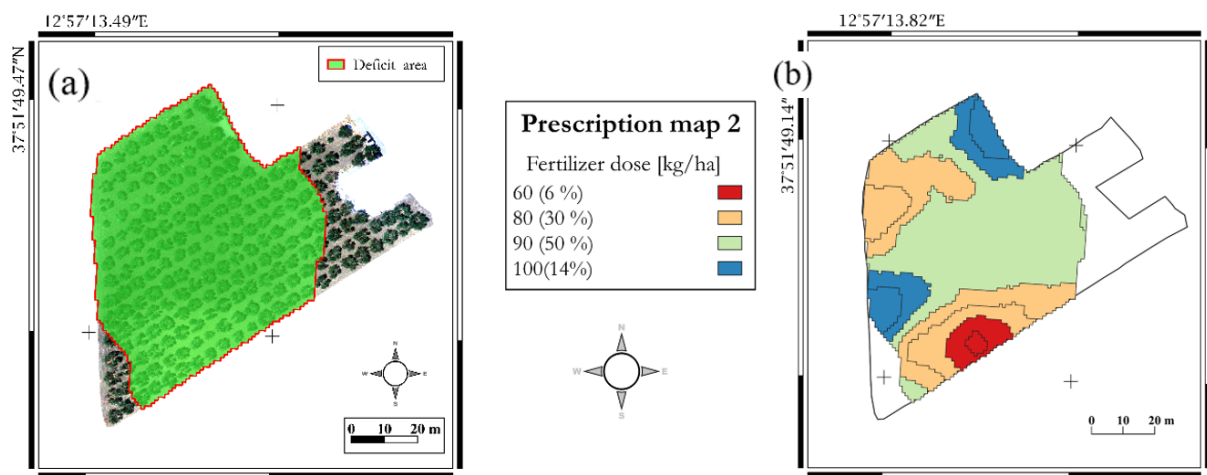


Fig. 3. (a) Deficit area with an average foliar nitrogen concentration per plant below the minimum threshold (1.2%). (b) Four different areas are represented with different colours.

Using the vegetative and spectral data estimated by drone, it was possible to determine the amount of fertiliser to be distributed by constructing a plant-specific nutritional balance. The

prescription map, carried out only for the area requiring fertilisation, made it possible to differentiate within it four different sub-areas with varying doses: 60, 80, 90 and 100 kg/ha (Figure 3b). The areas with lower and higher fertilisation requirements covered an area of approximately 6% and 14% respectively. While the medium-high and medium-low dose areas covered 50% and 30% of the entire area. By differentiating the distribution in four areas, a saving in the fertiliser doses to be applied in the field was obtained (Figure 4). Specifically, applying the standard fertilisation would have resulted in a fertiliser quantity of 58 kg (quantity of fertiliser to be distributed over 5,800 m² with a single dose of 100 kg/ha), using prescription map1 of 44 kg (5,800 m² × 0.76, corresponding to the area that required fertilisation, always applying a dose of 100 kg/ha), while applying the variable-dose prescription map2 would have resulted in 39 kg (corresponding to a dose of 67 kg/ha) being distributed (variable dose depending on the extent of the areas identified).

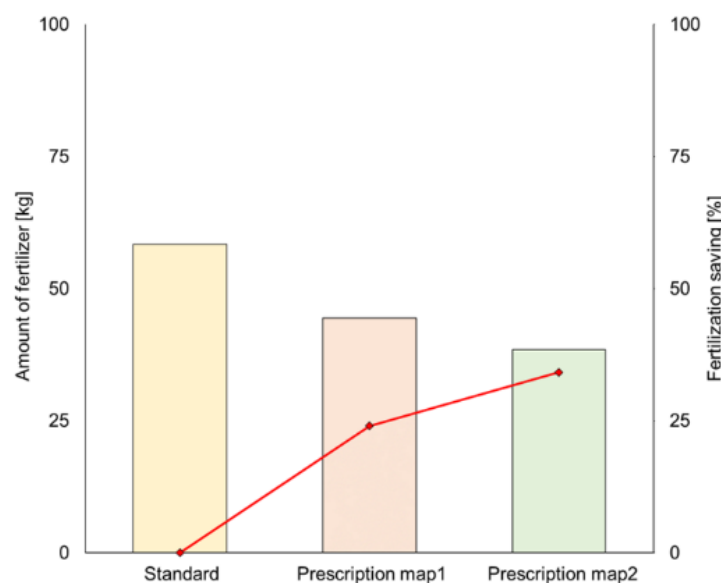


Fig. 4. Amount of fertiliser (kg, bar-plot) and fertiliser savings per hectare (kg/ha, red-line) calculated for the three different types of nitrogen fertiliser distribution (standard, prescription map1, prescription map2).

Therefore, as shows in Figure 4, with increased information available for creating a fertilisation plan, it is possible to create maps that can reduce doses and improve fertiliser use efficiency. Specifically, a fertiliser saving of 24 kg/ha (24%) and 33 kg/ha (33 %) was calculated using the first and second prescription maps, respectively. This increase in efficiency also leads to greater

economic and environmental sustainability for the olive orchards. This study confirms that a greater amount of information available per plant, considering growth and soil conditions, allows for greater fertilizer savings. The fertiliser savings obtained in this trial appear to be consistent with findings from other studies (López-Granados et al., 2004; Roma et al., 2023c; Van Evert et al., 2017).

Conclusions

The study conducted highlighted the potential offered by the use of drones with multispectral cameras for the construction of nitrogen fertilisation prescription maps. The results show that the multi-band images obtained from data processing provide information that correlates well with the physiological and productive status of plants and their variability in the field.

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Section 6. Final Remarks

This thesis shows that UAV-based multisource data are a powerful tool for PA. The combination of this data with ML and probabilistic frameworks underpin strategic agronomic decision-making across several agroecosystem.

- The literature review on horticultural systems gave a broad overview on the steady expansion of UAV applications and pointed to concrete benefits that go beyond proof-of-concept: high-resolution data, such as multispectral and thermal imagery, enables earlier diagnosis of crop stress, delineation of management zones, and site-specific interventions that reduce herbicides, fertilisers, pesticides, and water. Those reductions translate directly into cost savings and environmental benefits, and they also raise the quality of the evidence available to agronomists, technicians, and consultants when advising farmers. At the same time, the review underscores a practical constraint: the value of UAV data depends on reliable preprocessing, fusion, and interpretation, which still require specialised skills and computing resources. Continued development aimed at automation, processing speed, and user-oriented software is therefore essential to broaden access in production settings where innovations are adopted gradually.
- The case study of N management in potatoes illustrated how sensing and modelling can be combined into an operational pipeline. Integrating UAV multispectral imagery with ML and anchoring the estimates to a partially pooled hierarchical Bayesian formulation

of the CNDC, provided high-resolution NNI maps that detected N uptake and stress and consistently separated different N management regimes in the field experiments. The temporal dimension mattered: model outputs captured within-season changes in NNI and highlighted mid-season windows that were most informative for yield-related decisions. Because the Bayesian approach pooled information across sites, cultivars, and years while preserving local specificity, it produced robust estimates and credible intervals even when samples were limited or imbalanced. The combination of Bayesian inference, ML and UAV also clarified intra-field NR variations. The observed intra-plot variability points to interacting drivers, variations in soil properties, root distribution, water availability, and genotype-specific physiology. Quantifying those drivers is central to better understand crop NUE and constraining N leaching and nitrous-oxide emissions, which are strictly linked to excess or poorly timed N inputs. In practical terms, the pipeline provided spatially information directly translatable into prescription maps and into recommendations on how much, when, where to act. Future deployments should incorporate multispecies RS datasets, covering a wider range of canopy architectures and NUEs, and address operational scalability and processing cost of this approach.

- In olive groves, UAV multispectral surveys detected spectral and vigour responses attributable to pruning. These results potentially support variable-rate pruning and point toward greater automation as acquisition and analysis become more streamlined. The same multispectral imagery also supported construction of fertilization prescription maps aligned with plant physiological stress and productive status, demonstrating that UAV products can be used directly to design fertilisation strategies rather than serving only as diagnostics.
- In vineyards, multiple strands of evidence converged. Soil properties, particularly soil organic carbon and compaction, were found to be correlated to the historical vigour of cover crops and vine growth. When assessed over the long term through NDVI trends, these characteristics allow the identification of potential variability even before bud break. Pruning weight correlated significantly with multispectral indices and was mapped reliably with ordinary kriging, providing a practical proxy for canopy status before ripening. Structural sensing added a complementary, light-independent view: UAV-LiDAR reconstructed canopy architecture robustly, and LiDAR point density

correlated strongly with canopy and leaf area. In parallel, NDVI and thermal maps captured consistent patterns of vigour and canopy temperature, while hyperspectral reflectance accentuated spectral differences among varieties, supporting both physiological interpretation and variety discrimination. Together, the multi-sensor evidence shows that physiological and structural information are complementary and that their integration could improve both monitoring and management.

- Yield mapping in vineyards demonstrated how different components and multisource data could be brought into a single probabilistic framework. A hierarchical, partially pooled Bayesian model that fused UAV-based and Sentinel-based NDVI and grape-harvester telemetry produced accurate, high resolution yield maps accompanied by prediction uncertainty. The model captured a clear interannual differences in yield (on the order of 15%) consistent with weather pressure, while spatial yield patterns remained stable and aligned with pedological variation, evidence that the framework distinguishes transient climatic effects from persistent site effects. Uncertainty was not uniform: credible intervals widened near field boundaries and where predictors diverged, offering actionable guidance for targeted field checks. Generalisation is expected to improve as more seasons, fields, and cultivars are included, and as yield modelling is explicitly coupled with phenological models of berry development so that temporal dynamics are represented more mechanistically.
- Finally, another important piece of evidence emerged as a key determining factor for UAV-based yield estimates in vineyard: the design of field sampling protocols. Reframing the reference unit from individual vines to contiguous one-metre canopy segments in VSP systems preserves the geometric continuity of the productive wall and matches the 2D UAV footprint, reducing misalignment from vine spacing and canopy overlap. Across linear regressions, ML and a Bayesian estimator, the linear-based sampling strategy consistently outperformed vine-based sampled data, delivering higher accuracy ($R^2 \sim 0.78\text{--}0.84$; $\text{RMSE} \approx 0.26 \text{ kg}\cdot\text{m}^{-1}$) and narrower posterior uncertainty intervals at field scale; the advantage was most evident for the flight conducted at BBCH 73 and when spectral and geometrical UAV-based predictors (e.g., $\text{NDVI} \times \text{Fc}$) were combined. Practically, this shift in sampling unit provides a robust and scalable foundation for RS-driven, prescription-ready yield mapping in VSP vineyards, with

straightforward transferability to other perennial systems where canopy architecture governs the alignment between sensing and ground observations.

Collectively, the evidence in this thesis establishes UAV sensing, coupled with ML and Bayesian modelling, as a robust and scalable foundation for precision crop management. The resulting pipeline delivers accurate, uncertainty-aware products, including high resolution maps of NNI, NR, pruning weight and yield and translates them into actionable layers for fertilisation, irrigation, pruning and harvest. Beyond point accuracy, the framework preserves spatial structure, accounts for temporal dynamics, and provides auditability (data provenance, model parameters and uncertainty), enabling targeted scouting and supporting transparent, reproducible agronomy in other contexts. Looking ahead, it would be particularly valuable to investigate how the application of such spatially explicit algorithms compares with traditional uniform management in terms of resource-use efficiency and economic performance, as this would provide a clearer understanding of their practical benefits for growers.

The priority to improve the transferability of these results is clear. First, standardise and automate large-scale pre-processing. This includes radiometric and atmospheric correction, plus explicit cloud, shadow and illumination management. Optimise multi-sensor (RGB, multispectral, thermal, LiDAR) and multi-scale (UAV, satellite, proximal) fusion at acceptable costs and latency. Ensure coherence with harmonised field protocols and ground-truth sampling (reference unit, BBCH-aligned windows, sampling density).

Second, provide user-friendly tools that surface recommendations and uncertainties while hiding algorithmic complexity.

Third, broaden external validity by expanding training and validation across canopy architectures, cultivars, environments and N regimes, including low-input scenarios. Use shared protocols across sites and teams so that gains reflect agronomy rather than protocol differences. Fourth, integrate more phenological components using process-based models could potentially improve calibration under data scarcity conditions.

Future work should also focus on practical pathways for transferring these methods into operational workflows. A key scalability challenge is the need to run these models over large estates and multi-season datasets without excessive computational overhead. Integration with existing IoT infrastructures, such as soil-moisture probes, canopy temperature sensors and autonomous scouting platforms, would enable more frequent model updates and improve the

temporal alignment between sensor observations and management decisions. Together, these steps would support a realistic transition from research prototypes to field-ready decision tools. With these advances, the approaches outlined here become implementable at scale: reducing inputs and losses, improving the timing of interventions, and increasing confidence in field decisions, aligning agronomic performance with environmental sustainability.