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Abstract: Variable-rate nitrogen (VR-N) application allows farmers to optimize nitrogen (N) input site-specifically within field boundaries, enhancing both economic efficiency and environmental sustainability. In this study, VR-N technology was applied to durum wheat in two small-scale commercial fields (3–4 ha each) located in distinct agro-climatic zones of Thessaly, central Greece. A real-time VR-N application algorithm was used to calculate N rates based on easily obtainable near real-time data from unmanned aerial vehicle (UAV) imagery, tailored to the crop's actual needs. VR-N implementation was carried out using conventional fertilizer spreaders equipped to read prescription maps. Results showed that VR-N reduced N input by up to 50% compared to the conventional uniform rate N (UR-N) application, with no significant impact on wheat yield or grain quality. In one of the fields, VR-N led to a yield increase of 7.2%, corresponding to an economic gain of €164 ha^{-1}, while in the second field—where growing conditions were less favorable—no significant yield advantage was observed. Environmental benefits were also notable. The carbon footprint (CF) of the wheat crop was reduced by 6. 4% to 22.0%, and residual soil nitrate (NO_3^-) levels at harvest were 13% to 36% lower in VR-N zones compared to UR-N zones. These findings suggest a decreased risk of NO_3^- leaching and ground water contamination. Overall, the study supports the viability of VR-N as a practical and scalable approach to improve N use efficiency (NUE) and reduce the environmental impact of wheat cultivation which could be readily adopted by farmers.

Keywords: variable rate application; N management; UAV; near real time data; NDVI vegetation index; remote sensing

1. Introduction

Durum wheat (*Triticum turgidum* L. subsp. *Durum*) is one of the most important cereal species globally, a crucial staple crop in many arid and semi-arid regions around the world and its cultivation is concentrated in the Mediterranean Basin and the Great Plains of North American as well as in West and Central Asia [1]. In terms of production is the 10th most cultivated cereal globally, and its annual production ranges from 35 to 40 million tons, accounting for about 7% of the total wheat production [2,3]. With an average durum wheat production of 1.07 million tonnes (0.37 million ha growing area) during the last decade, Greece is among the top ten world's leading durum wheat producing countries [4,5].

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Wheat growers strive to maximize crop yields and at the same time to increase the protein content by applying the least amount of N fertilizer or better by spreading over well-adjusted in-season nitrogen (N) fertilization therefore, are called upon to balance at that point on the curve of maximum economic return where yield and protein are in the ideal ratio [6]. However, N fertilizers are commonly distributed in a uniform way across fields without considering in-field spatial and temporal variability [7]. The dominant practice for farmers is to apply a fixed rate of N fertilizer onto the whole fields and even entire farms. This also represents the prevailing fertilization practice among wheat growers in Greece resulting to irrational application of N-containing fertilizers which could be the cause of significant environmental and health problems through N gas emissions (NH_3, N_2O, NO), nitrates leaching (NO_3^-), surface runoff and erosion. In addition, excess N affects soil biodiversity, causes soil acidification, and affects air and water quality with harmful consequences for climate and human health [8–11].

Both over-fertilization and under-fertilization are quite damaging to crop production and product quality and require site-specific N management (SSNM). SSNM and precision agriculture can contribute to the sustainable management of crop production inputs by addressing the real needs of specific regions in the field rather than the average needs of whole fields [12]. Moreover, SSNM can increase the N use efficiency (NUE) at field scale [13–15] which has been confirmed for small to medium scale agriculture systems similar to Greek agriculture [6,16]. NUE in wheat production in Greece is around 30% which is low and similar to Swiss agriculture [6] but lower compared to Danish agriculture, for instance, showing a NUE of 41% [17]. Crop intensification coupled with excessive amounts of N fertilizer application and the ability of plants to uptake only around 50 % of the N applied have led to several environmental problems [18,19]. Among the factors that contribute to relatively low NUE are the uniform fertilizer N application rates to spatially and/or temporarily variable landscapes. It appears that the application of precision agriculture technologies and methods to increase NUE in wheat production can significantly reduce the environmental impact of agricultural production. Therefore, variable rate N application (VR-N) has been proved the potential to that improves NUE in small to large-scale agricultural cropping systems [20–22].

Even though studies have largely considered heterogeneity of large size fields, until now small-scale heterogeneity within fields (<1-2 ha) are typically neglected [6,23]. To achieve the goal of VR-N, fields should be treated on the basis of their smallest scale of significant variability. Small fields (<3 ha) representing the vast majority (87%) of the world's agricultural land, show great variability in yield [24,25]. Therefore, finding precision farming solutions for small-scale farms is essential. Also, 2/3 of EU agricultural holdings in 2016 were smaller than 5 ha in size [26]. Such pilot fields are represented in Thessaly (Greece) and the results will be usable by farmers (& comparable to other small-scale systems in EU-27 countries).

Unmanned aerial vehicles (UAV) are platforms suitable for monitoring fields of small to medium size and provide a number of possibilities and benefits for farmers. Among them are crop monitoring (high-resolution data on plant health), nutrient management (application of fertilizer according to the actual needs or even the individual needs of the plants) and yield mapping (data on the yield at different parts of the field) [27]. Higher-resolution UAV data may capture better within-field variability, enabling more precise fertilizer application, while coarser resolutions (i.e. 10 m) may smooth out spatial heterogeneity, potentially leading to suboptimal management decisions [28]. Purchase and the operational knowledge costs and the time needed to acquire and process the remote sensing data are considered some of the major drawbacks of UAV technology [29]. Even though precision fertilization methodologies and monitoring of the vegetation condition have been advanced, crop N-status quantification and fertilization support based on remote sensing imagery is still not fully standardized [30]. The reliability of image data provided by a UAV platform to non-destructively diagnose N status in wheat and to guide in-season VR-N has been provided by recent studies [6,31] but few studies are dealing with VR-N in small-scale farming systems and new sensing technologies in the literature.

Validated sensor-based algorithms for in-season N fertilization are presently being used in cereal production systems for improving yields and NUE [32]. Real-time VR-N, using the algorithm developed by Holland and Schepers [33], has been piloted in the region of Thessaly, Greece, demonstrating significant economic and environmental benefits. Reduced N inputs—without yield loss—led to improved NUE by the crops [22,34,35]. However, this practice typically requires advanced fertilizer spreaders capable of integrating specialized equipment, such as multispectral sensors and dedicated controllers. In the present study, VR-N application was implemented using the equipment already available to the farmer, by utilizing near-real-time data from UAVs, demonstrating a more accessible and scalable approach to precision fertilization.

The main hypothesis was that the application of SSNM using VR-N techniques would reduce average N application compared to the standard uniform fertilization strategy without affecting yield, grain quality and ultimately increasing NUE and reducing the risk of N surplus. The novelty of this work is that, except of the optimization of the N fertilization efficiency, and the fact that this is the first official VR-N application in wheat crop in Greece based on high spatial resolution data and UAV derived fertilizer maps, the proposed strategy, is friendly to use and it could be utilized by farmers employing the necessary equipment and by agricultural consultants. The objectives of the study were (i) to test the real-time VR-N Holland and Schepers [33] algorithm to calculate VR-N with near real time data and (ii) to increase knowledge on how data derived from a UAV platform representing temporal and spatial variability of crops can support VR-N application in durum wheat in small fields under Mediterranean conditions.

2. Materials and Methods

2.1. Locations and Experimental Management

Two commercial fields which are located in the south-east part of Larissa Prefecture, (Region of Thessaly) central Greece, under different agroclimatic zones were selected for this study in the growing season 2022-2023 (Figure 1). Field A in Agrokipio, (39°25'28"N, 22°42'15"E) occupies an area of 4.1 ha and field B in Ano Vasilika, (39°19'55"N, 22°34'1"E) occupies an area of 2.9 ha. The *Köppen-Geiger* climate type in the region of field A is a combination of cold semi-arid with dry and hot summers (*BSk*/*Csa*) and in the region of field B a Mediterranean climate with dry, hot summers (*Csa*) [36]. Topographic relief exhibits considerable heterogeneity between and within the two fields. Field A exhibits variable slopes, with the dominant category being from 0.1% to 5.0%, and its altitude varies from 143.6 m to 152.6 m above sea level. Field B exhibits greater slopes, which in many areas exceeds 10.0% and its altitude ranged from 263.9 m to 280.1 m above sea level (Figure 1).

The soil in field A is classified in the order of *Cambisols* and in field B in the order of *Calcisols* [37]. *Cambisols* are moderately developed soils with weak horizon differentiation. They are found at level to mountainous terrain in all climates and under a wide range of vegetation types and generally make good agricultural land and are used intensively. *Calcisols* are soils with a substantial secondary accumulation of lime. These soils are common in calcareous parent materials and found on level to hilly land widespread in arid and semi-arid environments. In terms of hydromorphy soils in field A are well-drained and are characterized as very deep (depth >150 cm) whereas, in field B the soils are very well-drained, with a depth that does not exceed 1 m (60-100 cm).

Composite soil samples (0–0.3 m depth, n = 16 in field A and n=20 in field B) were collected from each field prior to preplant fertilization. The samples were thoroughly mixed, air-dried, ground and after sieving, analyzed in the fine earth (<2 mm). Basic physicochemical soil properties of the two fields are compiled in Table 1. The soils of the fields were moderately fine-textured clay-loam (field A) or fine- textured clayey (field B) [38], with a slightly alkaline ($pH_{1:1}$ = 8.0) or medium alkaline soil reaction ($pH_{1:1}$ = 8.2) [39] and $CaCO_3$ content of 11.8 % and 27.1 % respectively [40]. The soil in field A was moderately sufficient (~10.0 mg P kg^{-1} soil) whereas, in field B was deficient (4.1 mg P kg^{-1} soil) in available phosphorous (P Olsen) [41]. Soil electrical conductivity (EC = <1.00 mS cm^{-1}, 25 °C) [42], soil organic matter (~1.5 %) [43] and total soil N (TSN = 0.1-0.2 %) were low in both fields. The

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method of ammonium acetate (1N at pH = 7) was used for exchangeable cations [44]. Exchangeable potassium (K^+) was found medium to low and was determined in a flame-photometer, and magnesium (Mg^{++}) was high in both fields as measured with an atomic absorption spectro-photometer (Varian Techtron). The soil-extractable by DTPA [45] zinc (Zn), iron (Fe) and copper (Cu) were medium and manganese (Mn) was high (>2.5 mg kg^{-1}) in both fields. Boron (B) in soils of both fields was found low (<0.5 mg kg^{-1}) [46].

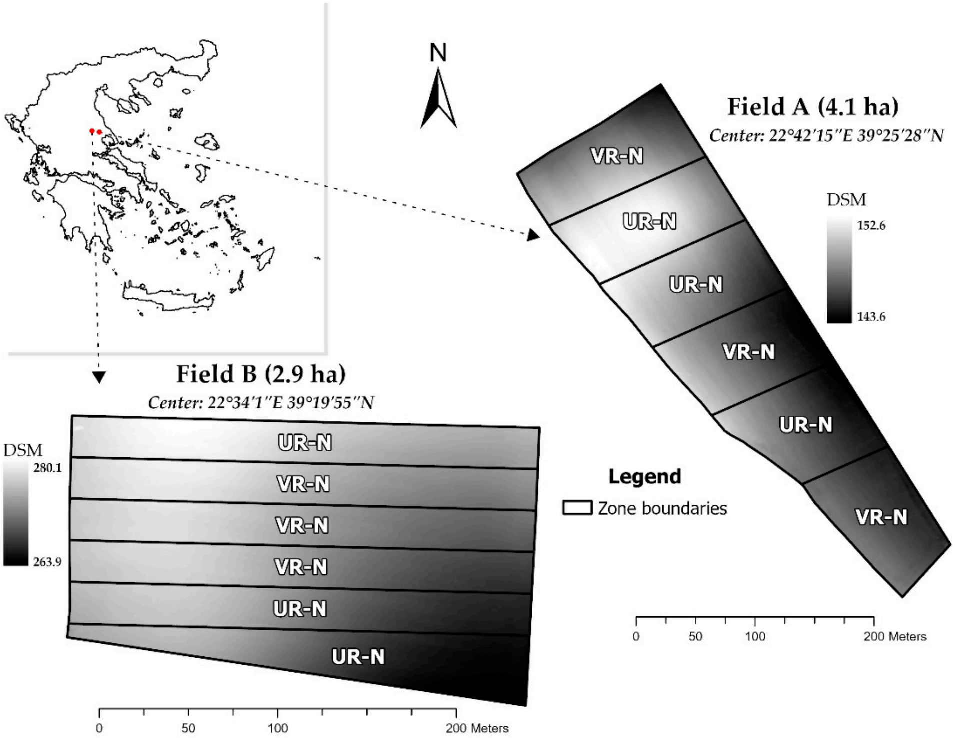

Figure 1. Location, size, dimension and representation of elevation data (Digital Surface Model - DSM) of the experimental fields (field A, Agrokipio and field B, Ano Vasilika) in Larissa Prefecture (central Greece) with delineated zones of uniform (UR-N) and variable-rate in season N application (VR-N).

Table 1. Soil classification and soil physicochemical properties (0-30 cm) prior to preplant fertilizer application of the two experimental fields.

	Field A	**Field B**
Location-Region	Agrokipio	Ano Vasilika
Soil Classification [1]	*Cambisols*	*Calcisols*
Sand (%)	36.6 ± 1.59	28.5 ± 1.20
Silt (%)	36.4 ± 1.02	48.6 ± 1.73
Clay (%)	27.0 ± 1.13	22.9 ± 1.30
Soil Texture	*Clay Loam* (CL)	*Clay* (C)
pH, (1:1)	8.0 ± 0.05	8.2 ± 0.02
EC [2]	0.62 ± 0.03	0.45 ± 0.02
SOM [3] (%)	1.4 ± 0.11	1.5 ± 0.11
$CaCO_3$ %	11.8 ± 2.18	27.1 ± 1.83
P_{Olsen} mg kg^{-1}	9.9 ± 1.83	4.1 ± 0.42
TSN [4] (%)	0.10 ± 0.01	0.11 ± 0.01
K^+ cmol kg^{-1}	0.4 ± 0.03	0.6 ± 0.06

Mg^{+2} cmol kg^{-1}	5.7 ± 0.18	6.2 ± 0.20
Cu [5]	0.9 ± 0.05	0.9 ± 0.03
Fe [5]	4.1 ± 0.31	3.6 ± 0.13
Mn [5]	8.8 ± 0.88	3.0 ± 0.11
Zn [5]	0.7 ± 0.04	0.6 ± 0.08
B mg kg^{-1}	0.4 ± 0.04	0.4 ± 0.03

[1] Soil order (WRB) [37], [2] EC = Electrical Conductivity (mS cm^{-1}) (25° C), [3] SOM = Soil Organic Matter, [4] Total Soil N, [5] DTPA extractable trace elements mg kg^{-1}. For average values reported: n = 16 in field A and n = 20 in field B (± stadard error of the mean).

Wheat sowing was performed on 18 November 2022 in field A (cultivar "Simeto") and on 21 November 2022 in field B (cultivar "Monastir") adopting 300 kg ha^{-1} of seed sowing density and 1.3 cm sowing depth in both fields. "Simeto" is an early maturing cultivar with medium tillering ability and pest and lodging resistance and excellent protein content. "Monastir" is a medium early cultivar known for its high to medium resistance to lodging and diseases and its high yields and quality. Field A has been managed to oregano for the past 3 years under no tillage. In field A, tillage operations included conventional ploughing (0.25 m), field cultivating (heavy type) and disking which were performed prior to wheat sowing. In field B the preceding crops were wheat, lentils and wheat in crop rotation under conventional tillage operations (ploughing, field cultivating - heavy type).

Based on the initial soil analyses the farmer in field A, applied preplant fertilizer uniformly (Nutriphos 16–20–0) at a rate of 200 kg ha^{-1} in mid-November (15.11.2022) and at field B applied preplant fertilizer uniformly (Slowtec 12–18–3) in 18.11.2022, at 220 kg ha^{-1} to provide adequate N supply during early season under P and K sufficiency.

In each location and field, the daily mean air temperature and monthly precipitation during the growing seasons were recorded via an energy autonomous integrated system for outdoor weather monitoring (Agenso AGIOT-0086 wireless weather station). In the 2022-2023 growing season precipitation in field A (18 November 2022 to 22 June 2023), was 427.2 mm and in field B (21 November 2022 to 30 June 2023) was 417.7 mm. Accordingly, season mean temperature was 11.6 °C in field A and 10.8 °C in field B.

The growing season of 2023 was relatively dry and at middle-heading (BBCH 55) [47] wheat in field A, received 82 mm of irrigation through a ''travelling gun'' irrigation system on 27.03.2023. No irrigation was applied in field B. Post-emergence systemic herbicide Mustang was sprayed for controlling broadleaf weeds on 15 March 2023 in field A and on 14 March 2023 in field B. Phytosanitary operations in field A included additionally Elatus Era fungicide which was sprayed on 19 March 2023. Both fields were managed without growth regulators.

2.2. Experimental Design, N Management and Data Acquisition

Each field was divided into six equivalent in size zones and N fertilization treatments were randomly assigned to each zone on a completely randomized experimental design. In season N fertilization with granular ammonium nitrate (NH_4NO_3 - 34.5–0–0, total N 34.5% - ammoniacal N, 17.0% and nitrate N, 17.5%) took place on 24 February 2023 in field A and on 09 March 2023 in field B. From an agronomic point of view, NH_4NO_3, is an excellent fertilizer because it combines two different N forms eventhought its low N content compared to other sources makes the transportation, storage, and application more expensive per unit of N. In each field half of the zones, received a uniform (UR-N) top dressing of granular NH_4NO_3 at the rate of 343 kg ha^{-1} when plants were at the mid-tillering stage (BBCH 24-25). As a usual practice of local wheat producers these are the recommended N fertilizer rates which are based on the assumed yield and target quality [grain protein content and N harvest index (grain N/total N uptake ratio)], taking into account the N applied during basal fertilization. The rest zones received variable-rate nitrogen (VR-N), using a two-disc fertilizer spreader, with a controlled doser (Rauch Axis M/H 30.2).

At physiological maturity (on 22 June 2023 in field A and on 30 June 2023 in field B, BBCH 92-93) wheat plants were cut at ground level using hand sickles and oven dried at 65 °C, until constant weight. Total above-ground biomass (TBY), 1,000 grains weight (TGW), grain yield (GY), grains m^{-2}, harvest index (HI) (ratio between grain dry weight and total dry weight), grain protein content GPC (%) and N grain yield (NGY) (gm^{-2}) were determined as the averages of fixed 3 subsamples (each of $1m^2$ sampling area) within the center in each of the 6 aforementioned N fertilizer treatment zones in each field. GY was converted into t ha^{-1} at 13% humidity. Harvested wheat grain samples were dried, weighed, ground into powder to measure the total N content using Kjeldahl digestion method [48]. The determination of grain crude protein content (GPC %) was carried out in triplicate samples of 0.5 g. Composite triplicate soil samples within each N treatment zone from the two fields were collected after plant wheat harvest of a depth 0-30 cm to determine soil residual nitrate N [49].

2.3. Low-Altitude Remote Sensing Data, VR-N Calculation and Fertiliser Application Maps

Few days before in season N application when plants have reached BBCH stage 24-25 (mid tillering), high resolution multispectral image data were taken (near real time data) with the UAV DJI Phantom 4 Multispectral RTK. The UAVs campaigns were conducted in clear, cloudless, and calm weather conditions between 10:00 am and 12:00 pm local time. Using the software DJI GS Pro (https://www. dji.com/cn/ground-station-pro/) flight routes were pre-planned and aerial photography performance in real-time during the flight was examined. The flight altitude was set at 120 m. From this altitude the spatial accuracy is 6.4 cm pixels which is considered very detailed for N fertilization. Moreover, this altitude provides a balance between image resolution and coverage. Image overlap was determinate for 80% front and side, to ensure sufficient redundancy for accurate photogrammetric reconstruction. Flying speed was 5 m s^{-1} to minimize motion blur while maintaining efficient coverage.

UAV imagery was proceeded with DJI Terra software for each field to generate Normalized Difference Vegetation Index (NDVI) which is based on differences in the red (670 nm) and near infrared (780 nm) spectrums for each entire field [NDVI = (NIR − red)/(NIR + red)] (Figure 2). We used the 95th percentile algorithm by Holland and Schepers [33] to calculate N application rates using a reference value of NDVI reflectance of the crop. The NDVI reference value was determined by the "virtual strip approach'' for the use of multispectral sensors [50]. Based on this approach, a portion (one strip) of the existing crop that represented the range in crop vigor within the field selected from the entire field NDVI values, and then statistically identified plants that are deemed to be non-N limiting by selecting the 95-percentile cumulative value from the histogram of NDVI values. The virtual strip approach has been applied for VR-N applications in wheat, cotton and corn cultivations demonstrating significant reductions in N fertilization [21,22,35]. The algorithm by Holland and Schepers [33] make use of a sufficiency index (SI = NDVI sensed/NDVI reference) and was applied for each pixel of the captured images to calculate the VR-N doses and to create fertilizer prescription maps. In our study SI was calculated from the NDVI values of the entire field. Fertilizer field maps were created using ArcGIS software (ArcGIS Desktop: Release 10 Redlands, CA, USA: Environmental Systems Research Institute) (Figure 2).

The dimension of the pixel-specific N fertilization values was 9m × 9m, which was chosen to match the operational range of the disc spreader (Rauch Axis M/H 30.2) that was mounted on the cultivation tractor (John Deere 5125R, USA). The tractor speed during fertilizations was kept constant at ~10 km/h. The tractor was equipped with a GEN4 4240 Universal Smart Touch terminal. It's AutoTrac™ and section control is capable and fully ISOBUS AEF certified. An active JDLink™ Connect subscription the display supported wireless data exchange with the John Deere Operations Center.

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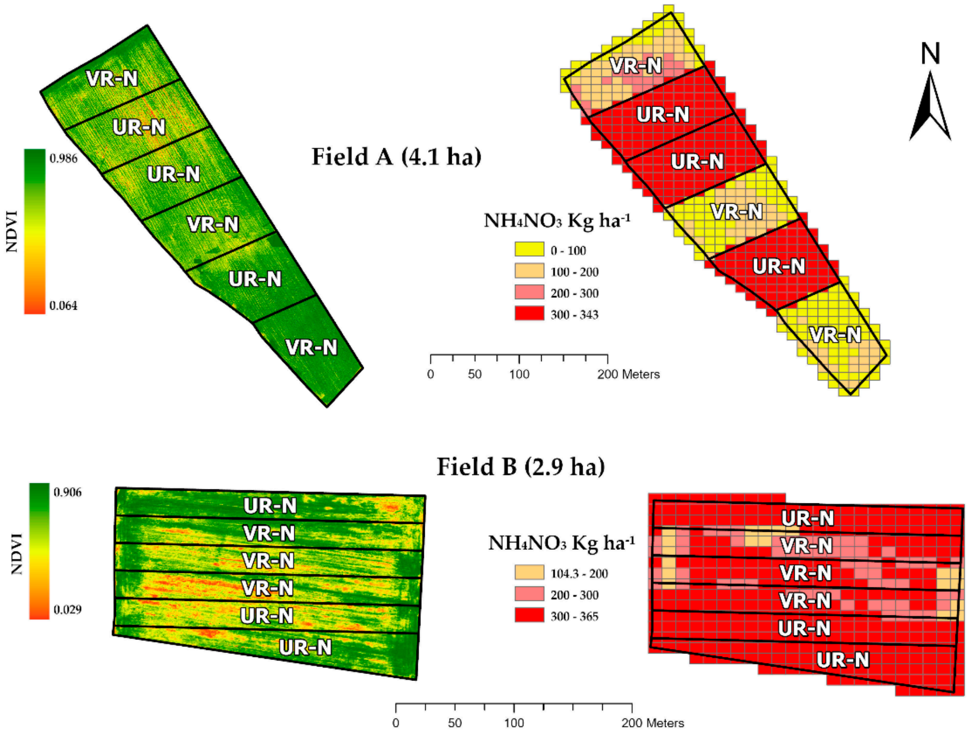

Figure 2. NDVI (Normalized difference vegetation index) map and corresponding pixel-oriented (9 m × 9 m) N fertilization map of the two fields in Larissa Prefecture (central Greece).

2.4. NUE, Environmental and Economic Assessment

NUE is a complex term and can be defined based on different components and specific indices. In this study we did not include N control (0 N) plots thus N production efficiency (NPE) serves as the proper index of NUE as it provides a measure of the total economic output as a result of N utilization from all sources of N including fertilizer and was calculated as follows [51].

$$\text{NPE (kg kg}^{-1}\text{)} = \text{GY/N fertilizer rate} \quad (1)$$

Where GY is the grain yield in kg ha^{-1} and fertilizer N rate is amount of fertilizer N applied in kg ha^{-1}.

The environmental evaluation of variable rate nitrogen (VR-N) application was conducted by estimating the carbon footprint (CF) of the crop, based on the model by Hillier et al. [52]. The CF was calculated in terms of kg CO_2 ha^{-1} and kg CO_2 tn^{-1} of harvested product, taking into account all field operations from soil preparation to harvest (tillage/seedbed preparation, pre-plant fertilization, seeding, irrigation, phytosanitary operations, and final harvest). Additionally, residual inorganic N levels after harvest were assessed as an environmental indicator, as this N remains unused by the crop and poses a potential risk of N losses from the root zone through leaching or gaseous emissions.

A simplified estimate the economic income, defined as the marginal return of N fertilization (MR, € ha^{-1}) was calculated in Equation 2 according to Wang et al. [53]. For the economic assessment (MR), we focused on the revenues from durum wheat production in € ha^{-1}, here defined as the difference between gross revenues minus N fertilizer costs. The economic comparison between the VR-N and UR-N was based on the calculation of the differences in revenues, fertilizer N costs, and grain yields between VR-N and UR-N.

$$\text{MR (€ ha}^{-1}\text{)} = \text{GY} \times \text{PY} - \text{Napp} \times \text{PN} \quad (2)$$

Where, GY is the grain yield (kg ha^{-1}), PY is the grain price (€ kg^{-1}), Napp is the N fertilizer applied (kg N ha^{-1}), PN is the N fertilizer price (€ kg^{-1}). Prices of fertilizers and grains in the experiment year were based on local prices. Comercial grain prices of durum wheat without defects

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and impurities were 0.4 € kg^{-1} and 0.37 € kg^{-1} for field A and B in Greece in 2023 respectively while, prices for fertilizers were 0. 775 € kg^{-1} and 0.848 € kg^{-1} for field A and B in 2023 respectively.

It must be highlighted that in field A in the southernmost zone (VR-N zone, Figure 1) during harvest we observed large areas of weed infection with wild oat (*Avena sterilis* L.) and wild mustard (*Brassica arvensis* L.) affecting wheat grain quality and commercial grain prices, therefore we have not considered data of this zone for calculating MR. This is considered a simplified economic balance between the cost of fertilizer and the gain from the sale of the grain to the mill because other field management costs such as seed, labor for fertilization, irrigation, mechanical sowing, the cost to obtain prescription maps or costs for the technology and the machinery were not taken into account.

2.5. Statistical Analysis

Statistical analysis of the data was processed using one-way ANOVA with SPSS (IBM Corp. Released 2023. IBM SPSS Statistics for Windows, Version 29.0.2.0 Armonk, NY: IBM Corp). Means of the examined parameters between the two sites were compared by calculating the smallest significant difference with the level of statistical significance ($p< 0.05$) [54].

3. Results

3.1. N Fertilizer Applied and Yield Related Components

N fertilizer application rates were on average reduced in the VR-N treatments by almost 20% to 50%, depending on the field. On average in field A, 170 kg ha^{-1} of fertilizer N was applied in VR-N zones was approximately half (50%) of the fertilizer N dose applied by the farmer in the UR-N treatment. In field B, 20% less fertilizer was applied in the VR-N zones (Table 2). Total dry biomass yield (TBY) in both fields showed no significant difference between the VR-N and the UR-N treatment and ranged from 13.9 t ha^{-1} (field B, VR-N) to 16.1 t ha^{-1} (field A, UR-N). In field B, GY showed significant difference between the two fertilizer treatments and was on average 17.4% lower in the VR-N compared to UR-N treatment whereas, in field A, GY showed no significant difference between the two fertilizer treatments. Correspondingly, TGW after harvest was significantly lower in the VR-N treatment compared to UR-N treatment in field B. Grains m^{-2} and HI (the ratio of grain to total shoot dry matter) showed no significant difference between the VR-N and the UR-N treatments in both fields. Grains m^{-2} and reproductive efficiency (HI) tended to be lower in the VR-N zones in both fields. The grain protein content (GPC) varied from 11.9 % (field A) to 12.4 % (field B) in the VR-N zones, while in the UR-N zones from 13.8 % (field A) to 11.6 % (field B). NGY showed also no significant difference between the VR-N and the UR-N treatments in both fields (Table 2).

Table 2. N fertilizer applied, yield, yield components and N related parameters for the two fields in Larissa Thessaly (Central Greece)

Field	N treatment	Napp	TBY	GY	TGW	Grains m^2	HI	GPC	NGY
A	VR-N	170	15.4	5.49	56.3	11511	34.6	11.9	10.1
	UR-N	343	16.1	6.35	51.7	13361	39.3	13.8	13.9
B	VR-N	280	13.9	5.42b	43.6b	13518	38.9	12.4	10.8
	UR-N	343	15.5	6.56a	49.5a	14548	45.0	11.6	12.2

VR-N, variable-rate nitrogen; UR-N, uniform rate N fertilizer; Napp, avg level of NH_4NO_3 applied (kg ha^{-1}); TBY, total biomass yield (t ha^{-1}); GY, grain yield (t ha^{-1}); TGW, thousand seed weight (g); HI, harvest index = the ratio of grain to total shoot dry matter (%); GPC, grain crude protein concentration (%); NGY, N gain yield (gm^{-2}); Means with different lower case letters are significantly different at $p<0.05$. Means with no letters are not significantly different.

3.2. N Efficiency and Financial Assessment

Compared to UR-N, the reduction of average applied N in the VR-N treatments resulted in significantly higher NPE in field A. The efficiency of grain production in relation to the N applied (NPE) was relatively low and showed almost no different performance between VR-N and UR-N in field B (Table 3).

The marginal returns (MR) of VR-N also showed improved financial gain, when compared to the UR-N treatment in field A. The improved gain of VR-N was 7.2% as compared to UR-N, which corresponded to 163.8 € ha^{-1} (ΔMR) mainly due to the reduction of the applied N fertilizer. However this difference was not statistically significant. In field A we have not considered one of the 3 zones in MR calculation due to lower quality grain affecting commercial prices. Adopting VR-N technology showed no financial gain (MR) in field B (Table 3).

Table 3. NUE as N production efficiency (NPE) and marginal return of VR-N for the two fields in Larissa Thessaly (Central Greece) for the 2022-2023 growing season.

Field	N treatment	Napp	NPE	MR	PY	PN	$\Delta G_{VR\text{-}N}$	ΔMR
A	VR-N	170	32.3a	2436.7 *	0.40	0.775	7.2	163.8
	UR-N	343	18.5b	2272.9				
B	VR-N	280	19.3	1825.8b	0.37	0.848	No gain	No gain
	UR-N	343	19.1	2136.7a				

VR-N, variable-rate nitrogen; UR-N, uniform rate N fertilizer; Napp, avg level of NH_4NO_3 applied (kg ha^{-1}); NPE, N production efficiency (kg kg^{-1}); MR, marginal return (financial gain) of N fertilization (€ ha^{-1}); PY, is the local grain price (€ kg^{-1}) in 2023; PN is the local N fertilizer price (€ kg^{-1}) in 2023; $\Delta G_{VR\text{-}N}$, is the improved gain of VR-N of N fertilization (%); ΔMR, difference in marginal return of VR-N vs UR-N, (€ ha^{-1}). Means with different lower case letters are significantly different at $p<0.05$. Means with no letters are not significantly different. * In field A average of MR for VR-N treatment was based on two out of 3 zones.

3.3. Environmental Assessment

The reduced N application rates achieved through variable rate technology resulted in a lower CF (expressed as kg CO_2 ha^{-1}) in both fields. Specifically, in field A, the CF was reduced by 22% compared to the uniform N application. In field B, the reduction was smaller, reaching 6.37%. When expressed as kg CO_2 per ton of yield (kg CO_2 tn^{-1}), the CF of the crop decreased by 5.3% in field A, while it increased by 13% in field B. This increase is primarily attributed to the lower yields observed in that field (Table 4).

Table 4. Carbon footprint (CF), and residual nitrate N (NO_3-N) after harvest for the two fields in Larissa Thessaly (Central Greece) of the 2022-2023 growing season.

Field	N treatment	CF (kg CO_2 ha^{-1})	CF (kg CO_2 tn^{-1})	Soil NO_3-N
A	VR-N	1859.3b	362.5	16.8b
	UR-N	2389.7a	383.0	26.3a
B	VR-N	2198.2b	407.0	14.6
	UR-N	2348.0a	360.1	16.9

Soil NO_3 – N, residual after harvest (kg ha^{-1}); Means with different lower case letters are significantly different at $p<0.05$. Means with no letters are not significantly different.

Residual soil NO_3-N was also significantly reduced under VR-N application. The reduction reached 36% in field A and 13.6% in field B, indicating that UR-N leave substantial amounts of unused N in the soil (Table 4).

4. Discussion

The current study deals with the performance comparison of VR-N with UR-N in durum wheat and introduces a method to determine the N application rates as well. For the latter, the 95th percentile algorithm by Holland and Schepers [33] was applied to NDVI images of the wheat canopy captured by UAV few days prior to fertilization. By this algorithm the calculation of the amount of N fertilizer that has to be applied to a specific area in the field depends, in addition to the foliage reflectance vegetation indices, (i.e. NDVI), on the growth stage of the crop at a given time, the total amount of N required by the crop and the amount of N that has already been applied. One of the benefits of using this algorithm is that information for estimating wheat N requirements is not based on soil or plant tissue analyses, but on the plant's own response to incident radiation, which includes any variations both spatially within the boundaries of a field and temporally from year to year [32.33,35]. The integration of the proposed algorithm with high-resolution UAV imagery and commercially available smart fertilizer spreaders offers a practical and accessible solution for implementing variable rate fertilizer applications, facilitating adoption by farm managers and agricultural consultants. The first step in SSNM is identifying within field variability whereas, the choice of sensor plays also a crucial role in shaping the fertilization strategy. UAVs for spectral data collection offer high spatial resolution and accuracy as also in our study where the spatial accuracy of 6.4 cm for the necessary bands for calculating the NDVI is considered very detailed for making N fertilization more accurate [55–58]. High-resolution sensors may be beneficial for fields with high spatial heterogeneity as demonstrated for the two fields in our study (differences in topographic relief, soil class, soil texture, % $CaCO_3$ content, available P, etc) (Figure 1, Table 1) whereas, lower resolution data might be sufficient for more uniform fields [28]. Moreover, the present study considered NDVI values of the entire field for calculating the sufficiency index [SI = $VI_{(NDVI)}$ sensed/$VI_{(NDVI)}$ reference] and ultimately VR-N doses, instead of using the SI of a portion (one strip) of the existing crop that represented the range in crop vigor within the field [59], a differentiation which may increase the robustness of the algorithm. Although the virtual strip approach by Holland and Schepers [50] has been applied with success for VR-N applications in wheat, cotton and corn cultivations demonstrating significant reductions in N fertilization under more or less similar pedoclimatic conditions [21,22,35], to the best of our knowledge this is the first ever study which applied the algorithm of Holland and Schepers [33] on high spatial resolution (accuracy of few cm) near real time data acquired by UAV to construct N fertilizer maps on wheat.

As far as the performance comparison between the two N treatments, the results proved that VR-N application reduced the total N application without any yield loss in one of the two pilot fields (field A) (Table 2) confirming results of other studies for small-to-medium-sized wheat agricultural systems [6,35,53]. TBYs were in the range of 13.9 t ha^{-1} to 16.1 t ha^{-1} and GYs were in the range of 5.42 t ha^{-1} to 6.56 t ha^{-1} and were comparable between the two fields. However, comparable GYs in the VR-N zones resulted from much higher on average N fertilizer application (additional 110 kg ha^{-1}) in field B as compared to field A. High resolution NDVI images captured few days before in season N fertilization showed that in field A plants were healthier (greener) compared to pants in field B. This in turn, is mirrored to the amount of N fertilizer calculated by the algorithm of Holland and Schepers [33] for in season N application (Figure 2).

In field A, underlying soil properties but also pedoclimatic conditions plus irrigation may have favored high soil N-mineralization rate during the vegetation period which led to a good grain filling and higher TGW in the VR-N treatment (Table 2).Contrarily to field A, in field B, GY and TGW in the VR-N treatment were significantly lower compared to UR-N treatment. These results may be attributed to high fluctuations of the relief of the topography and the greater slopes (reaching ~15%) in field B which affects water movement in soil, erosion of topsoil, and deposition. In steeper slopes reduced water retention and higher erosion rates, result in thinner and less fertile soils [60]. Moreover, soil in field B belongs in the order of *Calcisols* enriched with free calcium carbonate ($CaCO_3$ =27.1%, Table 1), which may be rather problematic under certain conditions for wheat crop production (i.e., limited availability of P and some of the trace elements such as Fe, Zn, and Cu). Application method of N did not significantly affected number of grains m^{-2}, HI, and NGY in both fields (Table 2). GPC (11.6–13.8%) was relatively lower compared to GPC that obtained by Stamatiadis et al. [35] in the same region, under three N treatments including VR-N, for durum wheat "Simeto" cultivar which has medium tillering ability and responds well to N fertilization.

Residual soil NO_3-N in the VR-N zones was lower than in the UR-N zones (36 % significantly lower in field A) suggesting that VR-N technology can potentially reduce the risk for groundwater pollution in the spring when precipitation exceeds crop water use and therefore can protect environmental resources as described also by other researchers [61–63]. Substantial amounts of unused N in the soil in UR-N zones has both environmental and economic implications, as it can contribute to N leaching and increased input costs without corresponding yield benefits. Based on a report from the Hellenic Ministry of Environment and Energy for the reference period 2016 – 2019 (Report on Directive 91/676/EEC) [64] efforts to rationalize the amounts of N applied with fertilizers during the past 3 decades in Greece based on the implementation of Council nitrates Directive 91/676/EEC (concerning the protection of waters against pollution caused by nitrates from agricultural sources) have not delivered the expected results. The same report indicated that there was no substantial change or there was even a small increase in the nitrate content in the surface waters on the 64.2 % of the sampling points of the monitoring network, while for groundwater the respective percentage exceeds 59.8 %. Moreover, advanced technology fertilizers (slow and controlled release fertilizers, nitrification and urease inhibitors, fertilizers with biostimulants, nanofertilizers etc) are ways to increase fertilizer use efficiency [65] however, the increased fertilization cost and the limited available data on their efficacy under different pedoclimatic environments suggest that the use of variable fertilization rate can be promising and more profitable way to reduce the total amount of N applied.

Most of the definitions developed for NUE, are based on grain yield, implying the input-output ratio of N fertilizers [66–68]. Basically is the ratio of biological yield (total aboveground plant dry matter or total plant N) or economic yield (grain yield or total grain N) and N supply (from soil, organic fertilizer or inorganic fertilizer), or soil plus fertilizer [69]. NUE indices have been basically denoted as agronomic efficiency (AE), physiological efficiency (PE), recovery efficiency (RE), N production efficiency (NPE) or partial factor productivity of applied N (PFP) and some other indices [66,70]. However, each index serves better in estimating NUE depending on the different cropping practices with the presence or not of no-N control plots [71]. As indicated previously our study did not involve control (0 N) plots thus NPE [or partial factor productivity of applied N (PFP)] serves as the proper index of NUE since it is adjusted for the GY with the direct application of the N supply under each treatment [72]. The ability of the crop to efficiently use the applied N fertilizer to increase grain yield (NPE, the ratio of grain yield and amount of fertilizer N applied) was significantly higher in the VR-N treatment only in field A. In field B there was almost no difference in NPE between VR-N and UR-N (Table 3). These results are attributed to the amount of the average N fertilizer applied in the VR-N zones in the two fields to achieve the respective comparable yields (5.49 kg ha^{-1} in field A vs 5.42 kg ha^{-1} in field B). As stated previously average GY in the VR-N zones in field B resulted from additional on average 110 kg ha^{-1} fertilizer as compared to field A (Figure 2). The higher N fertilization dose that was, on average, applied in the VR-N zones of field B—and which ultimately led to lower NPE compared to field A—can be attributed not only to the field's inherently poor soil fertility conditions, but also to suboptimal crop management practices by the farmer affecting crop establishment including irrigation, and phytosanitary operations. These factors likely affected canopy reflectance, as captured by the UAV, which serves as a reference from which a sufficiency index (SI) is calculated and consequently influenced the calculated VR-N doses. As emphasized by

Holland and Schepers [33] a fundamental prerequisite of their algorithm is that, in order to accurately determine the optimal N fertilizer rate, the crop must be free of any stressors other than N deficiency.

This is translated in a marginal return of N fertilization (MR, € ha^{-1}) of 2436.7 € ha^{-1} in field A whereas, in field B, MR was 1825.8 € ha^{-1} (Table 3). It should be mentioned that in field A low quality of wheat grain in one of the three VR-N zones, due to large impurities observed during harvest, resulted in very low commercial grain prices, therefore this zone was excluded from MR analyses. In this study the MR offers an economic balance between the cost of fertilizer and the gain from the sale of the grain to the local market and could offer a better insight as to how VR-N technology could be adopted by farmers. The improved gain of VR-N when compared to the UR-N is 7.2 % corresponding to 163.8 € ha^{-1} in field A (Table 3). These results are comparable with the financial gains obtained by Argento et al. [6] in small sized wheat farms under temperate conditions in Switzerland. On the other hand gains are higher compared to the total 4-year economic benefit (168.0 € ha^{-1}) coming from the saved funds for fertilizers (including P and K) due to an application of variable fertilizer rate of in a larger field in northern Lithuania [73]. Other researchers in Italy found no significant differences of the barley GY between fixed and variable rate technologies under controlled lysimeter experimental conditions and the variable rate fertilization method has been proved to be an alternative to traditional fertilization management (considering environmental impact) leading to a saving of 266 € ha^{-1} [74].

The EU requires a 30% reduction in greenhouse gas emissions by 2030 and the implementation of sustainable agricultural practices can greatly contribute towards this goal. In this respect the environmental benefits of VR-N application are significant, both in terms of reducing the CF and minimizing the risk of pollution caused by residual inorganic N that remains unused by the crop after harvest as found in the present study. N-based fertilizers, accounting for approximately 5% of global GHG emissions indicating that increasing NUE is considered among the most effective strategies to reduce emissions [75]. Previous research has acknowledged the environmental advantages of implementing more precise N management strategies at the farm level, particularly in terms of reducing N leaching and nitrous oxide (N_2O) emissions [76–78]. VR-N application represents a promising approach to managing spatial variability in soil nutrient availability and crop performance. By enabling more precise SSNM, this technology offers both economic and environmental advantages. As such, it holds potential for broader implementation. Conducting a regional-scale evaluation of VR-N could yield valuable insights into its environmental and economic impacts across broader agricultural landscapes. Such data would be instrumental for policy-makers seeking to promote site- and time-specific N management approaches that align with crop requirements.

Results of this study also revealed that under less favorable conditions (i.e. high slopes, low availability of P like field B) there is no financial gain from adopting VR-N. The simplified private economic benefits for farmers suggested herein explains that there is little economic motivation to use VR-N application, which may also explain the so far low adoption of these technologies in small scale agriculture in Greece. It turns that the realization of in-season based N recommendations will rely on whether or not farmers can obtain a return on their investment, government support by incentives and the complexity of using such systems as a whole. However, as stated in previous section this is a simplified measure for financial gain (marginal return) because the cost to obtain prescription maps or costs for the technology and the machinery were not taken into account. The future plans of this study is to develop a friendly user application that will apply the algorithm to aerial images that users will be allowed to upload and to export automatically prescription maps for VR-N.

5. Conclusions

This study demonstrated that implementing SSNM using a well-established VR-N algorithm [33], combined with near real-time UAV-derived data and VR-N fertilizer spreaders, effectively reduced N application rates and improved NUE (as expressed by NPE) compared to conventional

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UR-N fertilization. N inputs in VR-N zones were reduced by 20% to 50%, depending on field heterogeneity and crop management practices, without considerable yield loss. The findings highlight that site-specific conditions—such as soil properties, pedoclimatic factors, and general field management—play a crucial role in determining the effectiveness of VR-N technology. In the present study, the N application method did not significantly affect most yield components, harvest index (HI), or grain protein content (GPC) in either field, except for thousand grain weight (TGW) in Field B. A key strength of the proposed VR-N strategy is its practical applicability. It does not require specialized or expensive equipment—only a commercially available fertilizer spreader with variable rate capabilities, which already represents the majority of new equipment purchased by farmers. The algorithm capitalizes on the spatial variability of crop indices, which inherently reflect soil and climatic factors influencing final yield. A significant advantage of the approach is that the plant's spectral behavior integrates these factors, offering a robust indicator of crop performance. In addition to agronomic benefits, VR-N implementation may significantly reduce the CF of wheat cultivation and lower the risk of groundwater contamination. Residual soil nitrate (NO_3^--N) was consistently lower in VR-N plots compared to uniform rate (UR-N) zones, underscoring the environmental value of the approach. While the results are promising, they are based on a single season and two field trials, and further multi-year, multi-location studies are necessary to validate the findings under varying pedoclimatic and seasonal conditions. Future directions include the development of a user-friendly digital tool that applies the algorithm to UAV imagery uploaded by farmers and automatically generates prescription maps for VR-N application.

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Abbreviations

The following abbreviations are used in this manuscript:

UAV	Unmanned aerial vehicle
VR-N	Variable-rate nitrogen
UR-N	Uniform rate nitrogen
NDVI	Normalized difference vegetation index
SSNM	Site-specific N management
NUE	N use efficiency
NPE	N production efficiency
WRB	World reference base soil classification system
DSM	Digital Surface Model
CF	Carbon footprint
GPC	Grain protein content
TBY	Total above-ground biomass

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TGW	1,000 grains weight
GY	Grain yield
HI	Harvest index
NGY	N grain yield
AE	Agronomic efficiency
PE	Physiological efficiency ()
RE	Recovery efficiency
PFP	Partial factor productivity of applied N
VI	Vegetation index

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