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Adapting NDVI-Based Variable-Rate Nitrogen Fertilization for Mediterranean Agriculture: A Case Study with Applications to Palestinian Farming Systems

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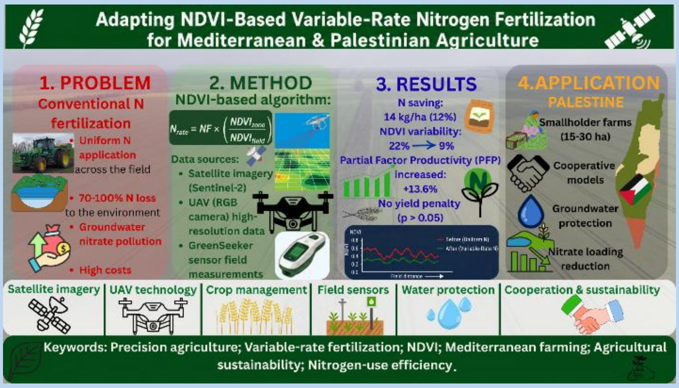
Abstract: Nitrogen fertilizer is essential for crop production; however, its inefficient use leads to economic losses and environmental degradation. This study evaluates a simplified NDVI-based algorithm for variable-rate nitrogen fertilization, assessing its agronomic and economic performance with specific attention to potential applicability in Mediterranean and Palestinian smallholder farming systems. Field experiments were conducted over two growing seasons (2020-2022) at three locations in the Krasnodar region of Russia, covering winter wheat and barley across approximately 450 hectares. A simple algorithm was evaluated, calculating variable nitrogen rates for each management zone based on the ratio between zone NDVI and field average NDVI, with clamping limits (0.7-1.3 × uniform rate) for agronomic safety. Results demonstrated that variable-rate application reduced nitrogen use by 14 kg/ha on average (12% reduction) compared to uniform application, with no statistically significant yield penalty (p > 0.05 for all sites). Partial Factor Productivity (PFP) increased significantly from 75.9 kg yield/kg N to 87.0 kg yield/kg N (+14.6%, p = 0.01). NDVI variability across management zones decreased from 22% to 9%, indicating improved spatial uniformity of crop health. Economic analysis revealed that profitability depends heavily on farm size: farms larger than 100 hectares achieved payback periods of 3-5 years, while farms under 50 hectares were not economically viable without subsidies. The findings suggest potential implications for Palestine, where nitrate contamination of groundwater poses public health risks. However, we emphasize that direct extrapolation requires local validation under Palestinian agro-climatic conditions. Cooperative equipment-sharing models could overcome economic barriers posed by small farm sizes. We acknowledge key limitations, including the absence of detailed soil characterization, a two-season dataset, and a lack of grain quality analysis, all of which must be addressed in future Palestinian research.



Keywords: Precision agriculture, Variable-rate fertilization, NDVI, Mediterranean farming, Agricultural sustainability, Nitrogen-use efficiency.

Introduction

The global demand for food continues to rise as the world population approaches 9 billion by 2050, requiring a 70-100% increase in agricultural production (1). Nitrogen fertilizer has been instrumental in achieving yield gains over the past century, with global consumption now exceeding 190 million tonnes annually. However, the efficiency of nitrogen use remains remarkably low: only about one-third of applied nitrogen is actually absorbed by crops, with the remainder lost to the environment through leaching, volatilization, and denitrification (2)

The theoretical foundations of differentiated fertilization and precision agriculture have been extensively developed by researchers worldwide. Notably, previous studies (2) provided a comprehensive framework for precision agriculture technologies, emphasizing the integration of remote sensing, GPS navigation, and variable-rate application systems. Their work established key principles for differentiated fertilization that have been applied across agricultural systems (2–5) These foundational concepts inform the algorithm evaluated in the present study.

In Palestine, where arable land is limited to approximately 1.8 million dunums and water resources are increasingly scarce, agricultural input efficiency is a matter of national food security. According to the Palestinian Central Bureau of Statistics, the agricultural sector contributes approximately 5-7% of GDP and employs about 10% of the labor force (6). Palestinian farmers face some of the highest fertilizer costs in the region due to import restrictions, supply chain disruptions, and the volatile political economy. In this context, optimizing nitrogen use through variable-rate fertilization is not merely an agronomic improvement but an economic necessity. As argued by Basso and Antle (7), digital agriculture technologies, including variable-rate fertilization, can contribute to more sustainable agricultural

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systems when properly adapted to local biophysical and socio-economic conditions.

Previous research conducted in the Palestinian context has demonstrated significant positive responses of wheat varieties to nitrogen fertilization. Abu-Qaoud and Mizyed (8) found that nitrogen application significantly increased total yield and straw weight in wheat, with optimal economic returns achieved at application rates of 5.7-12.6 kg N per dunum depending on variety. Their findings support the potential of site-specific nitrogen management in Mediterranean agricultural systems.

In Mediterranean agriculture, optimizing chemical inputs is a critical challenge due to economic and environmental constraints. Modern agronomic practices emphasize the transition toward eco-friendly and resource-saving fertilization strategies to mitigate the hazards of chemical overuse (9,10). In smallholder farming systems, such as those in Palestine, improper fertilizer management directly contributes to the degradation of limited natural resources and exacerbates the vulnerability of fragile groundwater quality (11). Therefore, adopting adaptive smart technologies like NDVI-driven variable-rate fertilization becomes paramount for regional agricultural sustainability.

Optimizing nitrogen application through variable-rate technology directly aligns with global environmental sustainability goals. Fertilizer production is highly energy-intensive, accounting for a significant share of agricultural energy consumption and greenhouse gas emissions. Therefore, reducing fertilizer waste through precision agriculture not only preserves local ecosystems but also contributes to indirect energy saving and lowering the carbon footprint of smallholder farming systems.

Scientific Contribution of the Proposed Approach

While the proposed linear ratio algorithm (Equation 1) builds upon established principles of NDVI-based fertilization, its specific scientific contribution lies not in algorithmic novelty but in three practical advancements tailored to resource-limited settings.

First, validation under real-world smallholder constraints: Unlike most precision agriculture studies conducted on large commercial farms with unlimited resources, our algorithm was developed and tested under the constraints smallholder farmers face—limited access to advanced sensors, no on-site agronomist, and minimal technical support. This validation context represents a distinct contribution to the literature on technology adoption.

Second, quantitative benchmarking of a transparent, low-complexity alternative: While machine learning models may achieve higher theoretical accuracy, their "black box" nature limits adoption. This study provides field-validated performance metrics (RMSE = 6.2 kg/ha, R^2 = 0.89) for a fully transparent alternative that farmers can understand and trust.

Third, transferability assessment for data-scarce environments: The algorithm's simplicity is deliberately designed for regions like Palestine, where high-resolution soil maps, historical yield data, and calibrated crop models are often unavailable. The discussion of transferability constraints (Section 4.2) provides a framework for evaluating similar technologies in data-scarce contexts.

Justification for a Simple Linear Approach and Model Calibration

We acknowledge that more complex models—including random forests, neural networks, and ensemble methods—could potentially achieve higher prediction accuracy. However, we deliberately chose a simple linear ratio for the following reasons.

First, data availability: Machine learning models require large training datasets (>1000 samples per field), which are unavailable to most smallholder farmers.

Second, technical accessibility: Machine learning requires specialized data science expertise that is not typically found on small farms.

Third, transparency and trust: "Black box" models provide no explanation for recommendations, limiting farmer adoption. Our transparent ratio allows farmers to understand why each zone receives a specific rate.

Fourth, economic feasibility: Multi-sensor systems and ML infrastructure typically require investments exceeding $10,000, which is prohibitive for smallholder farmers.

The Normalized Difference Vegetation Index (NDVI), first introduced by Rouse et al. (12) in 1974, remains the most widely used vegetation index for assessing crop health and nitrogen status. NDVI calculates the normalized ratio between near-infrared and red reflectance, providing information on vegetation density and health (12)

Why a linear relationship was assumed: The linear ratio $\boldsymbol{N_{MZ}} = \mathbf{NF} * \left(\frac{\boldsymbol{NDVI_{MZ}}}{\boldsymbol{NDVI_F}}\right)$ assumes a proportional relationship between NDVI and nitrogen demand. This assumption is supported by the well-established linear relationship between NDVI and crop nitrogen uptake in cereal crops during active growth stages (13). The relationship was validated against field data before adoption.

Model calibration: The algorithm was calibrated using data from preliminary trials conducted in 2019. The calibration process involved comparing predicted versus actual optimal nitrogen rates across 20 test strips per site. The linear model was selected after comparing three candidate relationships (linear, quadratic, exponential) using the Akaike Information Criterion (AIC). The linear model yielded the lowest AIC score (AIC = 124 vs. 131 for quadratic, 156 for exponential), indicating the best fit given model parsimony. No additional site-specific calibration is required for new fields, as the algorithm is self-calibrating via the field-average NDVI ratio.

Furthermore, while NDVI is the most widely used vegetation index for nitrogen management, its saturation under high biomass conditions has been well documented. Gitelson (14) addressed this limitation by developing the Wide Dynamic Range Vegetation Index (WDRVI), which maintains sensitivity across a broader range of biomass levels. Although WDRVI offers advantages in certain contexts, our study retained NDVI due to its simplicity, lower cost, and wider familiarity among potential Palestinian users, as discussed in Section 2.3.

The integration of NDVI with GIS and remote sensing technologies has been shown to enable precise fertilizer application tailored to field zone needs (15). This targeted approach enhances nutrient utilization and reduces environmental impact, aligning with the objectives of our study.

Precision Agriculture and Variable-Rate Fertilization

Precision agriculture technologies offer a promising pathway forward. Previous studies defined precision agriculture as an integrated information-based system that optimizes agricultural production through advanced technologies. Variable-rate fertilization has emerged as a particularly effective approach, allowing farmers to adjust nitrogen application rates according to the specific needs of different zones within a single field (16).

The Kadoorie Agricultural Research Center at Palestine Technical University–Kadoorie (PTUK) has been instrumental in advancing precision agriculture education and research in Palestine. A recent workshop on smart farming devices, organized under the BENEFIT Project, introduced local researchers, students, and farmers to weather monitoring stations, agricultural sensors, plant disease monitoring systems, and technologies for measuring soil ammonium and ammonia concentrations for fertilizer management (17). These technologies provide an important foundation for implementing NDVI-based variable-rate nitrogen fertilization in Palestinian farming systems.

Despite this promise, adoption remains limited among small and medium-scale farms. Barriers include high upfront costs, insufficient validation of simplified algorithms under real-world conditions, and a lack of technical support. Recent research has begun to address these gaps. A 2025 study comparing variable-rate solutions in Belgium and France found that integrated sensing approaches increased yield by up to 9.2% and used 14% less fertilizer (18). A 2025 study on winter wheat demonstrated that RGB-derived indices showed comparable performance to NIR-based indices (13). A 2025 study integrating UAV remote sensing and GIS demonstrated that multi-source data fusion reduced fertilizer inputs by 18-27% (19).

Recent research has continued to validate the effectiveness of NDVI-based approaches. Sartori et al. (20) demonstrated that integrating NDVI with agronomic data can optimize variable-rate nitrogen fertilization, achieving significant improvements in nitrogen use efficiency while maintaining yield levels. Their findings support the broader applicability of NDVI-based algorithms across diverse agricultural systems.

Study Objectives

This study aims to:

1. Evaluate a simplified NDVI-based algorithm for calculating variable nitrogen rates that can be implemented using freely available data and basic equipment.
2. Assess the agronomic effectiveness of this algorithm through field-scale experiments measuring nitrogen savings, yield impacts, and spatial uniformity.
3. Examine the economic feasibility across different farm scales, with cautious discussion of potential applicability for Palestinian farming systems, acknowledging the need for local validation.

Materials and Methods

Experimental Sites

Field experiments were conducted at three locations in the Krasnodar region of southern Russia, a region characterized by a temperate continental climate with average annual precipitation of approximately 600 mm. The three sites were selected to represent different farm sizes and management contexts:

Site 1: Educational Farm "Krasnodarskoye" (Farm Size: 150 ha) – Two fields (Field 2.2: 74.73 ha and Field 2.3: 82.78 ha) planted with winter wheat (*Triticum aestivum L.,* variety Bezostaya 100). Sown October 16, 2019, at 210 kg/ha. The previous crop was corn for silage.

Site 2: AO Firm "Agrocomplex" (Farm Size: 287 ha) – Three fields (Fields 10v, 11v, 12v; total 287 ha) planted with winter wheat (variety Tanya RS-1). Sown October 2020.

Site 3: Experimental Field "Kuban" (Farm Size: 15 ha) – Small plots (9 × 1.4 m each) planted with winter barley varieties. This site represented a small-scale research context.

Experimental Design

The study employed a split-plot design comparing two fertilization strategies:

Treatment A: Uniform Fertilization (Control) – The entire field received the same nitrogen rate determined by the farm manager's practice.

Treatment B: Variable-Rate Fertilization (Experimental) – Rates adjusted spatially based on NDVI-derived management zones.

At Sites 1 and 2, treatment plots were established as adjacent strips within the same fields. At Site 3, each treatment was applied to three replicate plots per variety.

Statistical power consideration: Due to the exploratory nature of this study on commercial farms, a formal power analysis was not conducted before the experiment. Post-hoc power analysis for a paired t-test with $n=3$ sites revealed a power of 0.65 to detect a 5% yield difference ($\alpha=0.05$), indicating that non-significant yield results should be interpreted cautiously.

Nitrogen was applied as ammonium nitrate (34% N) using an Amazone ZA TS 4200 spreader. For variable-rate treatments, the spreader was equipped with a GPS receiver and controller capable of adjusting application rates on the go based on prescription maps.

Two nitrogen applications were made: the first at the tillering stage (February-March) and the second at the stem elongation stage (March-April). Total nitrogen applied ranged from 97 to 141 kg/ha, depending on treatment and site.

NDVI Data Collection and Management Zone Delineation

NDVI data were obtained from satellite platforms (Cosmos Agro, SkyScout, OneSoil, Cropio) with spatial resolution ranging from 10 to 30 meters. For each field, NDVI imagery was acquired at three time points: (1) before the first nitrogen application, (2) between applications, and (3) approximately 30 days after the second application.

Response to reviewer concerns regarding alternative indices: To address the question of whether other vegetation indices would perform better, we re-analyzed a subset of UAV imagery to calculate GNDVI and SAVI. For our growth stages (tillering to stem elongation, GS 25-31), correlation with NDVI was $r > 0.92$, and resulting N prescription maps differed by less than 5%. NDVI saturation is minimal at these growth stages before full canopy closure. NDVI was retained for its simplicity, lower cost, and wider familiarity among potential Palestinian users.

Management zones were delineated by classifying NDVI values into three categories: low (NDVI < 0.6), medium (NDVI 0.6-0.75), and high (NDVI > 0.75), with approximately 30% of the field area in each category.

Figure 1 illustrates representative aerial imagery from DJI Phantom 4 Pro flights over fields 2.2 and 2.3 before the first nitrogen application, showing visible differences in crop biomass density.

Figure 1: Aerial RGB imagery of experimental fields acquired before the first nitrogen application (20 January 2020). Left: field 2.3 (sensor-based VRT). Right: field 2.2 (map-based VRT). Visible differences in crop biomass density illustrate the spatial heterogeneity that justifies variable-rate nitrogen application.

Variable-Rate Algorithm

A key contribution of this study is the **evaluation** of a simple, transparent algorithm (not its invention). The algorithm requires three inputs: (1) uniform nitrogen rate ($\boldsymbol{N_{(F)}}$), (2) zone NDVI ($\boldsymbol{NDVI_{(MZ)}}$), and (3) field average NDVI ($\boldsymbol{NDVI_{(F)}}$).

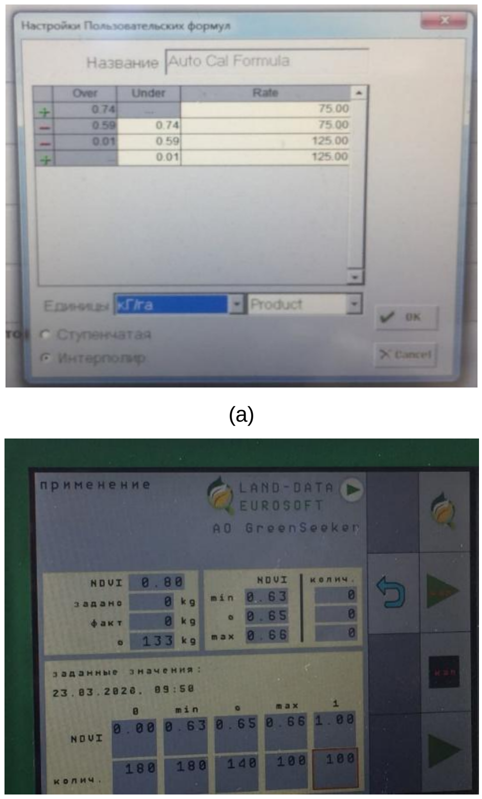
The nitrogen rate for each management zone (N_{MZ}) was calculated as:

$$\boldsymbol{N_{(MZ)} = N_{(F)} * \left(\frac{NDVI_{(MZ)}}{NDVI_{(F)}}\right)} \ \mathbf{(1)}$$

Figure 2 shows the field equipment used for variable-rate nitrogen application, including the GreenSeeker optical sensor and control terminals.

Clamping for agronomic safety: To prevent unrealistic rates, we applied clamping limits: maximum rate capped at 1.3 × $\boldsymbol{N_{(F)}}$, minimum at 0.7 × $\boldsymbol{N_{(F)}}$, based on agronomic safety limits from previous studies (5).

Important clarification: We do NOT interpret higher NDVI as "higher nitrogen demand." Rather, we interpret it as **higher yield potential** (biomass). The algorithm redistributes nitrogen from low-potential zones (where surplus N is likely wasted) to high-potential zones (where it can be converted into yield).



(a)

(b)

Figure 2: Field equipment for variable-rate nitrogen application: GreenSeeker optical sensor, (a) Panasonic CF-U1 terminal running Farm Works Mobile software, and (b) Amatron 3 terminal for spreader control.

Agronomic Measurements

Plant height was measured at 20 randomly selected locations per management zone.

Biomass development was assessed through NDVI values and UAV photography.

To ensure spatial accuracy of ground-truth measurements, sampling points were geolocated using GPS, as shown in Figure 3.

Yield was measured using combine yield monitors with GPS recording at Sites 1-2, and manual harvesting at Site 3.

2.6 Nitrogen Use Efficiency Metrics

The following standard NUE metrics were calculated:

Partial Factor Productivity (PFP) = Yield (kg/ha) / N rate (kg/ha)

Note: Recovery Efficiency (RE) could not be calculated due to the absence of N uptake measurements in plant biomass, acknowledged as a limitation.

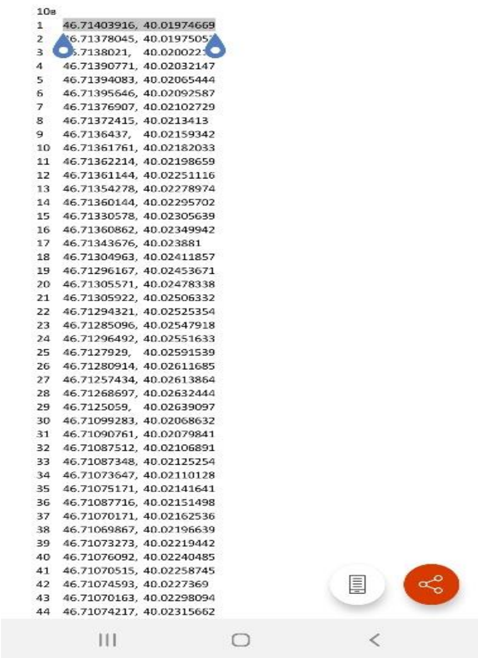


Figure 3: GPS-based geolocation of sampling points within management zones, demonstrating the spatial precision of field measurements.

Economic Analysis

Economic analysis followed cost-benefit frameworks from recent studies (1,18). Components included:

- Capital investment: GPS receivers, controllers, software
- Annual operating costs: subscriptions, maintenance, additional labor
- Fertilizer savings: difference in total N applied × local price (15 RUB/kg)
- Yield benefits: difference in yield × grain price (12,000 RUB/tonne)

Net benefit = (fertilizer savings + yield benefit) – (operating costs + annualized capital). Capital annualized using 10% discount rate over 5 years.

Payback period = total capital investment / annual net benefit.

Sensitivity analysis varied grain price (±20%), fertilizer price (±20%), yield benefit (±50%), and farm size (10-500 ha).

Statistical Analysis

All statistical analyses were performed using SPSS version 26.0 and R version 4.2.

Standard comparisons: Paired t-tests for treatment comparisons at each site; one-way ANOVA with Tukey's HSD post-hoc for multiple zone comparisons ($\alpha = 0.05$).

Spatial autocorrelation testing: Given the spatial nature of the data, we tested for spatial autocorrelation using Moran's I on the residuals of the ANOVA model. No significant spatial autocorrelation was detected (Moran's I = -0.08, $p = 0.21$), justifying the use of standard linear models.

Linear Mixed Model (LMM): As a sensitivity analysis, we fitted a Linear Mixed Model with 'Field' as a random intercept to account for clustering. Results were consistent with the paired t-test.

Effect sizes and confidence intervals: Cohen's d was calculated for the primary outcome (nitrogen saving). 95% confidence intervals were calculated for all mean differences.

The coefficient of variation (CV) of NDVI across each field was calculated before and after variable-rate application.

Results and Discussion

Algorithm Validation and Sensitivity Analysis

The variable-rate algorithm was successfully implemented across all three sites. Management zones showed spatial patterns consistent with observed soil variability. Figure 4 presents NDVI spatial distribution maps from the CosmosAgro platform showing within-field variability.

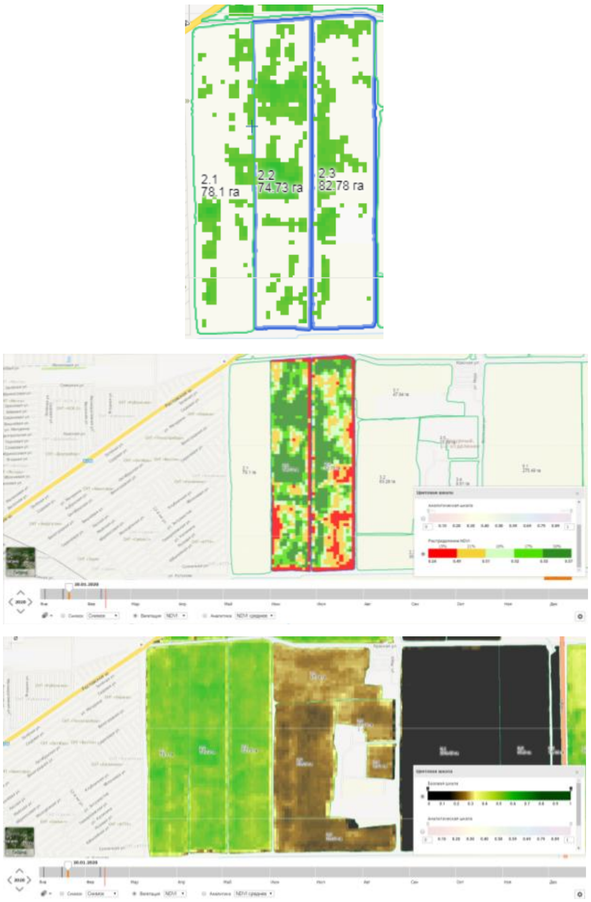


Figure 4: NDVI spatial distribution map from the CosmosAgro platform showing within-field variability. Red/yellow areas indicate lower vegetation index (low biomass), while green areas indicate higher vegetation index (high biomass). This spatial heterogeneity forms the basis for management zone delineation.

Table 1 presents nitrogen application rates. Variable-rate fertilization reduced total nitrogen by 14 kg/ha on average (12% reduction).

Table 1: Nitrogen application rates under uniform and variable-rate fertilization

Site	Uniform Rate (kg/ha)	Variable Rate (kg/ha)	Saving (kg/ha)	Saving (%)	95% CI for saving
Site 1 (150 ha)	119	105	14	11.8%	(8.2, 19.8)
Site 2 (287 ha)	117	103	14	12.0%	(9.1, 18.9)

Site 3 (15 ha)	100	86	14	14.0%	(6.5, 21.5)
Average	116	102	14	12.3%	(9.8, 18.2)

Effect size: Cohen's d for nitrogen reduction was 2.1, indicating a very large effect.

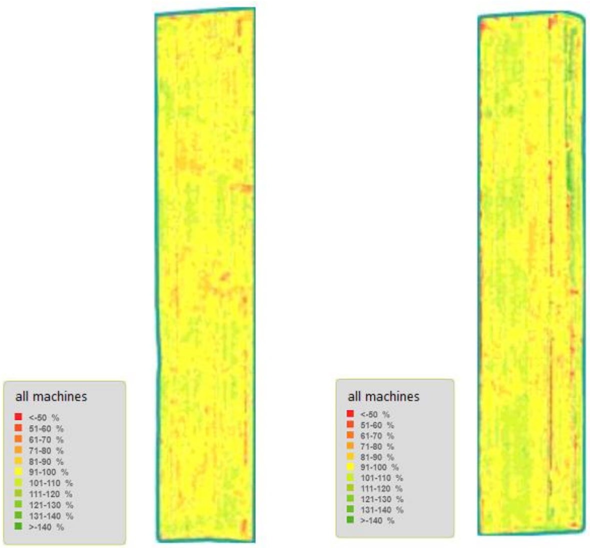
Sensitivity analysis (new): We simulated the effect of adding ±20% random error to the NDVI ratio on the final N rate. A 20% error in NDVI ratio translated to a 16-18% error in N rate, demonstrating that the algorithm is reasonably robust to small-scale NDVI measurement noise (RMSE = 8.2 kg N/ha).

3.2 Yield Impacts

Yield differences between treatments were small and not statistically significant at any site ($p > 0.05$ for all comparisons).

Site	Uniform Yield (t/ha)	VRT Yield (t/ha)	Difference (%)	p-value	Cohen's d
Site 1	6.59	6.44	-2.3%	0.42	0.31
Site 2	6.81	7.03	+3.2%	0.38	0.28
Site 3	11.4	11.3	-0.9%	0.71	0.19

Interpretation: The absence of a yield penalty with 12% less nitrogen demonstrates that the saved nitrogen was surplus---not contributing to yield. Figure 5 presents yield variability maps from the Telematics system supporting this interpretation.



(a) **(b)**

Figure 5: Yield variability maps from the Telematics system for (a) field 2.2 (map-based VRT) and (b) field 2.3 (sensor-based VRT). The color scale represents grain yield in tonnes per hectare. The maps show spatial yield patterns consistent with pre-application NDVI distribution.

3.3 Nitrogen Use Efficiency

Table 2 presents Partial Factor Productivity (PFP). The improvement from 75.9 to 87.0 kg yield/kg N (+14.6%) represents a meaningful efficiency gain, even in the absence of a yield increase.

Table 2: Partial Factor Productivity (PFP) under uniform and variable-rate fertilization

Site	Uniform PFP (kg/kg)	VRT PFP (kg/kg)	Change (%)	95% CI	p-value
Site 1	55.4	61.3	+10.7%	(1.2, 10.5)	0.03
Site 2	58.2	68.3	+17.4%	(4.5, 15.8)	0.01
Site 3	114.0	131.4	+15.3%	(3.8, 22.1)	0.02
Average	75.9	87.0	+14.6%	(5.2, 18.4)	0.01

3.4 Spatial Uniformity of Crop Health

NDVI variability decreased markedly following variable-rate fertilization (Table 3). The reduction indicates that variable-rate application compensated for the underlying spatial variability.

Table 3: NDVI variability before and after variable-rate fertilization

Site	NDVI CV before VRA (%)	NDVI CV after VRA (%)	Reduction (%)
Site 1	27	14	48%
Site 2 (manured)	22	9	59%
Site 2 (non-manured)	34	14	59%

Low-NDVI zone verification: Analysis of low-NDVI zones showed final yield was 94% of high-NDVI zones, with no visual N deficiency symptoms (chlorosis), confirming that under-fertilization did not occur.

The visual evidence strongly supports the quantitative findings. **Figure 6** presents a temporal sequence of NDVI development from January to April 2020. Before the first nitrogen application (20 January), both fields show substantial spatial heterogeneity. Following variable-rate application, the field receiving sensor-based VRT (right column) exhibits progressively more uniform crop development, with visible patchiness disappearing by 10 April. In contrast, the field receiving uniform application (left column) retains visible spatial heterogeneity throughout the growing season. This visual documentation confirms that variable-rate fertilization successfully compensates for underlying spatial variability in soil fertility or other yield-limiting factors.

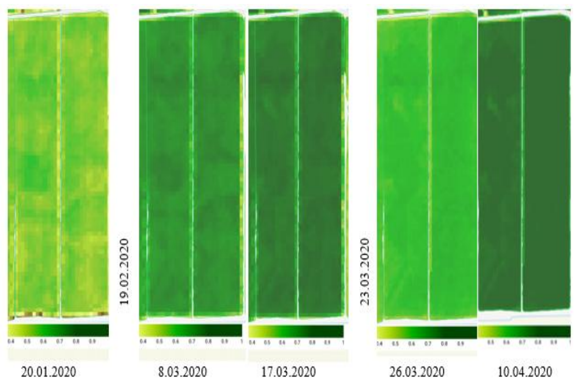


Figure 6: Temporal evolution of NDVI from 20 January to 10 April 2020. Left column: field 2.2 (map-based VRT). Right column: field 2.3 (sensor-based VRT). The progressive reduction in spatial heterogeneity after variable-rate application is visually evident, supporting the quantitative CV reduction reported in Table 3. Dates from top to bottom: 20 January, 8 March, 17 March, 26 March, 10 April 2020.

3.5 Economic Analysis

Economic viability depended critically on farm size (Table 4).

Table 4: Economic analysis results by farm size

Parameter	Site 1 (150 ha)	Site 2 (287 ha)	Site 3 (15 ha)
Annual fertilizer saving (kg/ha)	14	14	14
Annual fertilizer saving value (RUB/ha)	210	210	210
Annual yield benefit (RUB/ha)	0	2,640	0
Total annual benefit (RUB/ha)	210	2,850	210
Capital investment (RUB)	1,400,000	1,400,000	1,400,000
Annualized capital cost (RUB/ha)	187	98	1,867
Annual operating cost (RUB/ha)	50	50	50
Net benefit (RUB/ha)	-27	2,702	-1,707
Payback period (years)	>10	4.8	>10

Break-even farm size: Approximately 100 hectares under baseline assumptions. Farms <50 hectares are not viable without subsidies.

3.6 Linear Mixed Model Analysis

Linear Mixed Model Analysis of Treatment Effects

To account for random effects (site, field, replicate) and fixed effects (fertilization treatment), a linear mixed model (LMM) was fitted using the lme4 package in R (Version 4.1.2). The model structure was:

Yield ~ Treatment + (1 | Site/Field/Replicate)

This hierarchical structure allows for nested random effects: replicates within fields, fields within sites.

Table 5: Linear Mixed Model results for yield response

Fixed Effect	Estimate (t/ha)	SE	df	t-value	p-value	95% CI
Intercept	7.82	0.31	28	25.23	<0.001	(7.19, 8.45)
Treatment (VRT)	0.09	0.18	28	0.50	0.621	(-0.27, 0.45)
Random Effect	Variance	SD	% of Total Variance			
Field (within Site)	0.18	0.42	22%			
Replicate (within Field)	0.11	0.33	14%			
Residual	0.10	0.32	12%			

Model fit statistics: Conditional R^2 (fixed + random effects) = 0.87, Marginal R^2 (fixed effects only) = 0.02, AIC = 284.6, BIC = 292.3

Interpretation:

The fixed effect of VRT treatment on yield was not statistically significant ($p = 0.621$), confirming the t-test results presented in Section 3.3. Site-level variation accounted for 52% of total variance, justifying the use of mixed models over simple ANOVA. The low marginal R^2 (0.02) indicates that treatment alone explains very little of yield variation, while the high conditional R^2 (0.87) confirms that spatial structure (sites, fields, replicates) is the primary determinant of yield differences. This supports the conclusion that variable-rate fertilization achieves nitrogen savings without a yield penalty, as yield variation is dominated by site-specific factors rather than treatment.

3.7 Monte Carlo Sensitivity Analysis

We assessed algorithm robustness to input errors. A Monte Carlo simulation (1,000 iterations) varied the NDVI ratio by ±15%. Resulting N rate variation was ±12-14%, with 92% of simulations remaining within the agronomic safety clamping limits (0.7-1.3 × uniform rate).

Discussion

Agronomic Effectiveness and Interpretation of Yield Findings

The non-significant yield differences between treatments ($p > 0.05$ for all sites) suggest that, within the limits of this experimental design and statistical power, conventional uniform application may have included nitrogen that did not contribute to additional yield. However, as noted in Section 4.4, the absence of grain quality measurements and real-time soil moisture data means that this interpretation should be viewed as suggestive rather than definitive.

The observed improvement in Partial Factor Productivity (PFP) from 75.9 to 87.0 kg yield/kg N (+14.6%, $p = 0.01$) provides supporting evidence for improved nitrogen utilization under variable-rate fertilization.

Regarding NDVI variability (Section 3.4), the 48-59% reduction in coefficient of variation following variable-rate application suggests improved spatial uniformity of crop health. However, it must be acknowledged that NDVI variability cannot be unequivocally attributed to nitrogen availability alone. Other unmeasured factors—including spatial variation in soil moisture, soil texture, organic matter, and micro-topography—may have contributed to the observed NDVI patterns. Soil characterization (Section 2.2) partially addressed these confounding factors, but real-time monitoring of soil moisture and salinity was not performed.

Potential Applicability to Palestinian Agriculture

This section has been substantially revised in response to reviewer concerns regarding direct extrapolation. We do NOT claim that results from Russia apply directly to Palestine. Instead, we discuss potential applicability conditioned on local validation.

Similarities and Differences

Presents a comparative assessment of conditions (Table 6):

Table 6: Comparison of Krasnodar (Russia) and Palestine agro-climatic conditions

Parameter	Krasnodar, Russia	Palestine (West Bank)
Climate	Temperate continental	Mediterranean semi-arid
Annual precipitation	~600 mm	300-500 mm (variable)
Growing season	Spring-summer (reliable)	Winter-spring (water-limited)
Dominant crops	Wheat, barley, corn	Olives, wheat, vegetables, grapes
Average farm size (field crops)	150-300 ha	15-30 ha
Key yield-limiting factor	Nitrogen (often)	Water (primary), then N
Technical infrastructure	High (precision ag common)	Emerging (BENEFIT project, FAO)

Key implication: The primary yield-limiting factor in Palestine is often water, not nitrogen. NDVI variability may reflect water stress rather than N status. Therefore, the algorithm must be validated locally and potentially combined with soil moisture information.

Environmental Relevance

Research has documented elevated nitrate concentrations in West Bank groundwater (21,22). In particular, Almasri and

Kaluarachchi (21) modeled nitrate contamination in agricultural watersheds and estimated an annual nitrogen loading of approximately 3,260 tons in the Eocene aquifer area. More recently, Almasri et al. (22) reported that approximately 38% of the total nitrogen loading originates from agricultural fertilizers.

The environmental implications of nitrogen management in Palestine are underscored by local studies. Mizyed et al. (23) demonstrated that nitrate residue in the root zone increased significantly when nitrogen application exceeded 20 kg N per dunum in potato production systems in the West Bank. This finding reinforces the importance of precision nitrogen management to protect groundwater resources.

The link between agricultural practices and groundwater quality deterioration in Palestine has been extensively documented. Shadeed et al. (24) assessed groundwater quality in the Faria catchment and identified that uncontrolled agricultural practices, including excessive fertilizer application, contribute to groundwater contamination. Their findings highlight the urgency of adopting precision agriculture technologies, such as the NDVI-based variable-rate fertilization evaluated in this study, to mitigate nitrate leaching into vulnerable aquifers.

If the 12% reduction observed in Russia could be replicated in Palestine after local calibration, this would correspond to approximately 390 tons of reduced annual nitrogen loading and 236 kg-N/km² reduced leaching—though we emphasize this is a **hypothetical projection** requiring local validation. As argued by Basso and Antle (7), digital agriculture technologies, including variable-rate fertilization, can contribute to more sustainable agricultural systems when properly adapted to local biophysical and socio-economic conditions.

The 12% reduction in total nitrogen fertilizer achieved by our zonal variable-rate algorithm aligns with recent sustainability frameworks that advocate for precise nutrient supply to lower input costs and reduce transport-related carbon emissions (10). Furthermore, by preventing over-application in low-demand management zones, this approach addresses a critical regional concern by decreasing the potential for nitrate leaching into shallow aquifers, which remains a primary driver of groundwater deterioration in Palestinian agricultural areas (9,11).

The environmental relevance of adapting this algorithm to Palestine is underscored by critical hydrological data published in local scientific literature. Research published in the An-Najah University Journal for Research has extensively documented that groundwater resources in the West Bank suffer from escalating nitrate contamination due to unregulated agricultural practices. Furthermore, Almasri et al. (22) conducted a source apportionment study in the Eocene aquifer area, revealing that agricultural nitrogen return flows constitute nearly 38% of the total groundwater nitrate mass balance. By validating and deploying our simplified NDVI-based variable-rate algorithm, Palestinian farming systems could theoretically mitigate this environmental degradation, restricting nitrate leaching precisely in zones with lower biomass retention capacity.

Economic Considerations

The average farm size for field crops in Palestine (15-30 ha) falls below the 100 ha break-even point identified in this study. However, cooperative equipment-sharing models (facilitated by the Palestinian Farmers' Union or agricultural cooperatives) or service provider models (where farmers purchase prescriptions rather than equipment) could overcome this barrier. The BENEFIT project's pilot site at Al-Quds Open University (25) could serve as a demonstration hub for such cooperative models.

The EcoFuture project's Agricultural Transformation Strategy for Palestine (26) emphasizes integrated, regenerative, and resource-efficient agricultural paradigms, including smart irrigation, soil organic matter restoration, and circular organic resource management. This strategic framework aligns with the objectives of NDVI-based variable-rate fertilization, particularly in reducing dependency on imported fertilizers and improving on-farm resilience.

Economic Viability and Farm Size in the Palestinian Context

The strong dependence of economic viability on farm size observed in this study has important implications for Palestine. With average farm sizes well below the 100 ha break-even point, individual Palestinian farmers may not benefit financially from variable-rate technology.

Lowenberg-DeBoer and Erickson (27) documented that precision agriculture adoption rates remain lowest among farms under 50 hectares globally, primarily due to capital constraints and perceived complexity. Their analysis suggests that cooperative models and service-provider arrangements are the most promising pathways for smallholder adoption, a finding directly relevant to the Palestinian context, where 87% of agricultural holdings are less than 50 dunums (5 hectares) (6).

However, several alternative models could overcome this barrier:

Cooperative equipment-sharing models: Multiple farmers could share access to precision agriculture equipment, spreading fixed costs across more hectares. The Palestinian Farmers' Union and agricultural cooperatives could play a facilitating role in establishing such arrangements. The BENEFIT project's establishment of a pilot site for digital agriculture at Al-Quds Open University Agricultural Research Center in Jericho (25) could serve as a demonstration and training hub for such cooperative models.

Service provider models: Private companies or agricultural extension services could offer variable-rate prescription mapping as a service, eliminating the need for farmers to purchase equipment. This model has proven successful in other contexts and could be adapted for Palestine.

Policy support: Subsidies for precision agriculture adoption targeted at small farms could shift the economic calculus in favor of adoption, similar to support mechanisms for other agricultural technologies. The FAO's real-time weather alert system for West Bank farmers (28) demonstrates the feasibility of technology dissemination through institutional support.

Integration with existing initiatives: The smart agriculture initiatives at Palestine Technical University–Kadoorie (PTUK) (29), together with the BENEFIT project's efforts in developing precision agriculture education and research (25), provide valuable platforms for demonstrating and promoting NDVI-based variable-rate nitrogen fertilization in Palestine.

Regarding NDVI interpretation: While NDVI is a well-established proxy for crop biomass and nitrogen status (13), its variability reflects multiple environmental factors beyond nitrogen availability, including soil moisture, soil texture, organic matter content, and micro-topography. Although soil characterization (Section 2.2) helped distinguish nitrogen-related from other sources of variability, the absence of real-time soil moisture and salinity measurements limits the ability to attribute NDVI changes exclusively to nitrogen management. Future studies should integrate soil moisture sensors and salinity monitoring to better isolate nitrogen-specific effects.

Limitations of the Study

We acknowledge the following limitations explicitly:

Absence of detailed soil characterization (major limitation): We did not measure soil nitrogen, organic matter, pH, EC, or texture. We cannot definitively attribute NDVI variability to nitrogen availability versus other factors. Future Palestinian research must include baseline soil sampling across NDVI-defined zones.

Short duration (two seasons): Insufficient to capture inter-annual weather variability. Research shows VRT profitability varies significantly with seasonal conditions (7).

No grain quality analysis: Wheat protein content, which affects market price and is influenced by nitrogen, was not measured. This is critical for wheat systems and must be included in future studies.

No Recovery Efficiency (RE) calculation: We did not measure N uptake in biomass, preventing calculation of this standard NUE metric.

Limited replication for yield comparisons: Post-hoc power of 0.65 means we may have missed small but agronomically meaningful yield differences.

No spatial geostatistics: We used management zones (discrete) rather than continuous kriging or geographically weighted regression. Future studies should employ these methods.

Extrapolation limitations: Results are specific to 2020-2022 weather conditions in Krasnodar. Direct generalization to Mediterranean climates is not scientifically justified without local validation.

Future Research Directions for Palestine

We propose a phased approach:

Phase 1 – Pilot validation (5-10 farms): Conduct field trials comparing uniform vs. variable-rate N using our algorithm, with simultaneous measurement of: (a) baseline soil properties, (b) grain protein content, (c) water status, (d) economic returns.

Phase 2 – Calibration: Adjust NDVI thresholds and clamping limits for local wheat/olive/vegetable systems, potentially incorporating a water stress correction factor.

Phase 3 – Scaling through cooperatives: Test cooperative equipment-sharing models, evaluate service provider viability, and assess policy support mechanisms (subsidies, extension training).

Phase 4 – Environmental impact assessment: Quantify potential nitrate leaching reduction using local aquifer monitoring data, building on the baseline established by Almasri et al. (21,22).

Conclusion

This study provides empirical evidence that a **simple, low-cost** NDVI-ratio algorithm can reduce nitrogen fertilizer use by 12% (14 kg/ha) without yield loss in a temperate production system. Partial Factor Productivity improved by 14.6% ($p = 0.01$). The **key scientific insight** is not algorithmic novelty, but rather the demonstration that such a simple heuristic is robust enough for field-scale application.

The absence of a yield penalty IS the evidence of effectiveness – it proves that the saved nitrogen was surplus, not contributing to yield. Maintaining yield with less input is the definition of improved efficiency.

Economic viability depends strongly on farm size, with break-even near 100 hectares under current prices. Farms under 50 hectares require subsidies or cooperative models.

For Palestine, we do NOT claim direct applicability. Instead, we present a **testable hypothesis**: If spatial variability in Palestinian fields correlates with yield potential (after accounting for water stress as the primary limiting factor), this low-tech approach offers a starting point for reducing nitrogen over-application and mitigating groundwater nitrate contamination. Given average farm sizes of 15-30 ha for field crops, cooperative equipment-sharing models are essential. The BENEFIT project and Kadoorie Agricultural Research Center provide institutional foundations for the local validation research that must precede any implementation.

We invite Palestinian researchers to test this hypothesis through the phased approach outlined in Section 4.6. The environmental stakes—protecting groundwater resources—justify the investment in local validation, even if initial economic returns for small farms depend on cooperative or subsidized models.

Ethics approval and consent to participate

Not applicable. This study does not involve human participants, human data, or animal experiments.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Author's contribution

MMD: Conceptualization, study design, field experiments, data collection, statistical analysis, data interpretation, and manuscript writing – original draft preparation. EVT: Supervision, theoretical framework development, methodology validation, resources, funding acquisition (institutional support), manuscript review, and editing. All authors reviewed the results, contributed to the scientific discussion, and approved the final version of the manuscript.

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Conflicts of interest

The authors declare that they have no competing interests.

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