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Abstract

Super-high-density (SHD) olive production systems necessitate precise nutritional diagnostics to ensure sustained productivity, particularly under the restrictive nutrient availability conditions typical of calcareous soils. This research evaluated nutrient imbalance patterns and their correlation with yield and NDVI-derived canopy vigor across two olive cultivars (*Olea europaea* L. ‘Arbequina’ and ‘Koroneiki’) within SHD orchards in the Tarom region of Iran. Leaf nutrient composition was appraised using three distinct diagnostic frameworks: The Diagnosis and Recommendation Integrated System (DRIS), the Deviation from Optimum Percentage (DOP), and Compositional Nutrient Diagnosis (CND), employing high-yielding orchards as the reference population to establish nutritional norms. To correlate canopy-scale physiological status with foliar nutrient data, the Normalized Difference Vegetation Index (NDVI) was derived from Sentinel-2 satellite imagery. The analysis revealed consistent nutritional dysfunctions in low-productivity orchards across all three diagnostic approaches. Phosphorus (P) and potassium (K) emerged as the primary limiting macronutrients, while deficiencies in zinc (Zn), copper (Cu), and boron (B) represented the most significant micronutrient constraints, largely influenced by high soil pH and calcium carbonate content. Nutritional balance indices, namely NBI, Σ DOP, and CND-r², exhibited inverse relationships with both fruit yield and NDVI, indicating that increasing nutritional deviation significantly impairs both canopy development and economic output. Ultimately, the synergy between leaf-based nutrient diagnosis and remote sensing facilitates more precise monitoring and identification of nutritional constraints, thereby enabling optimized nutrient management in SHD olive systems.

Keywords: CND, DRIS, NDVI, Nutrient management, Olive nutrition, Remote sensing, SHD orchards

1. Introduction

The olive tree (*Olea europaea* L.) is one of the most important perennial crops in Mediterranean and semi-arid agroecosystems, where it plays a crucial role in rural economies and sustainable agricultural development. Olive oil is widely recognized as a functional food due to its high content of monounsaturated fatty acids, phenolic compounds, and antioxidant molecules that contribute to human health¹. To meet rising global demand, cultivation has shifted from traditional methods toward high-density (HD) and super-high-density (SHD) intensive hedgerow systems, which enhance mechanization and accelerate yield². However, these intensive systems intensify competition for light, water, and nutrients, affecting canopy architecture and physiological performance³. Consequently, inadequate management often prevents these orchards from reaching their potential, with an estimated 70% of SHD orchards producing yields below their genetic capacity⁴.

Among the factors influencing productivity in intensive orchards, plant nutrition represents one of the most critical determinants of tree growth, fruit development, and oil yield. High tree density increases the demand for essential macronutrients such as nitrogen and potassium while simultaneously altering the balance of micronutrients within plant tissues⁵. When nutrient supply is not properly adjusted to these increased physiological demands, nutrient imbalances may occur, leading to reduced photosynthetic activity, impaired reproductive development, and significant yield losses. In extreme cases, nutritional disorders may reduce orchard productivity by 60–70%⁶.

Reliable diagnosis of plant nutritional status is essential for developing effective fertilization strategies. Although soil analysis provides useful information about nutrient availability, leaf tissue analysis remains the most accurate indicator of the actual nutritional condition of the plant⁸. Traditional interpretation methods based on critical concentration ranges often fail to account for the complex interactions among nutrients within plant tissues. To overcome these limitations, several multivariate diagnostic approaches have been developed, including the Diagnosis and Recommendation Integrated System (DRIS), Deviation from Optimum Percentage (DOP), and Compositional Nutrient Diagnosis (CND)⁹. Among these methods, CND has received increasing attention because it considers nutrient concentrations as compositional data and evaluates the relationship between each element and the geometric mean of the entire nutrient system¹⁰. This

statistical framework allows a more comprehensive assessment of nutrient balance and facilitates the detection of both deficiencies and excesses that may not be evident through conventional analysis¹¹.

In Mediterranean olive-growing regions, B and Zn deficiencies have been identified as major limiting factors for olive productivity. Similar nutritional constraints have been reported in various horticultural crops in Iran, where elevated nutrient imbalance indices have been associated with reduced yields. At the same time, advances in precision agriculture have introduced new opportunities for integrating plant nutrition diagnostics with remote sensing technologies¹². These advancements highlight the need to assess how conventional nutrient diagnostic frameworks perform under different agro-ecological contexts, particularly in modern high-density olive systems.

This research addresses a critical knowledge gap by focusing on the Tarom region of Iran—a representative area characterized by calcareous soils, semi-arid conditions, and saline irrigation—where the cultivation of intensive cultivars, such as ‘Arbequina’ and ‘Koroneiki’, is rapidly expanding. Despite this expansion, comprehensive studies integrating multivariate nutrient diagnosis with remote sensing indicators remain limited in such distinct agro-climatic settings. To bridge this gap, the novelty of this study lies in implementing a multi-methodological diagnostic approach that integrates DRIS, DOP, and CND to enhance the reliability of nutritional evaluations. Furthermore, this work serves as an exploratory pilot to investigate the potential of Sentinel-2 derived NDVI as an auxiliary tool, aiming to establish an empirical link between canopy reflectance and leaf nutrient profiles. We hypothesize that: (H1) lower-yielding orchards will exhibit significantly higher nutrient imbalance indices than high-yielding ones; (H2) the three diagnostic methods will yield broadly consistent nutrient limitation profiles; and (H3) NDVI will show a significant negative correlation with nutrient imbalance indices. Ultimately, this study aims to evaluate the nutritional balance of these cultivars, identify key macro- and micronutrient limitations affecting regional olive productivity, and investigate the relationship between leaf nutrient indices and NDVI-derived canopy vigor to provide a robust scientific basis for optimizing fertilization management in intensive olive orchards.

2. Methodology

2.1. Description of study area

The super-intensive olive orchards examined in this study are located in the Tarom region of Qazvin Province in northwestern Iran, positioned near 36°44' N latitude and 49°23' E longitude (Fig. 1). The orchard consists of several separate planting blocks laid out across gently sloping alluvial ground, where small variations in elevation and surface texture create a naturally diverse field pattern. Olive trees are spaced 4.0×1.8 m apart and trained in a hedgerow configuration, a system widely adopted in high-density plantations to improve light interception and facilitate mechanical and manual management operations. The climate of the area reflects the characteristics of a Mediterranean regime, with an annual mean temperature of about 15 °C and roughly 450 mm of precipitation, most of which occurs during the colder months of the year¹³. The soils supporting the orchard are classified primarily as Inceptisols with Calcaric properties, developed on alluvial–colluvial deposits typical of semi-arid foothill environments in this part of Iran. Management practices in the orchard involve shallow tillage performed twice a year and the use of regulated drip irrigation throughout the active growing season. Pruning is carried out in February, and the removed branches are shredded and incorporated into the soil to help increase organic matter inputs and maintain soil quality. Continuous monitoring and pest-control measures are also implemented to preserve tree health and ensure that canopy appearance and physiological condition remain unaffected by biotic stress (<https://www.swri.ir>).

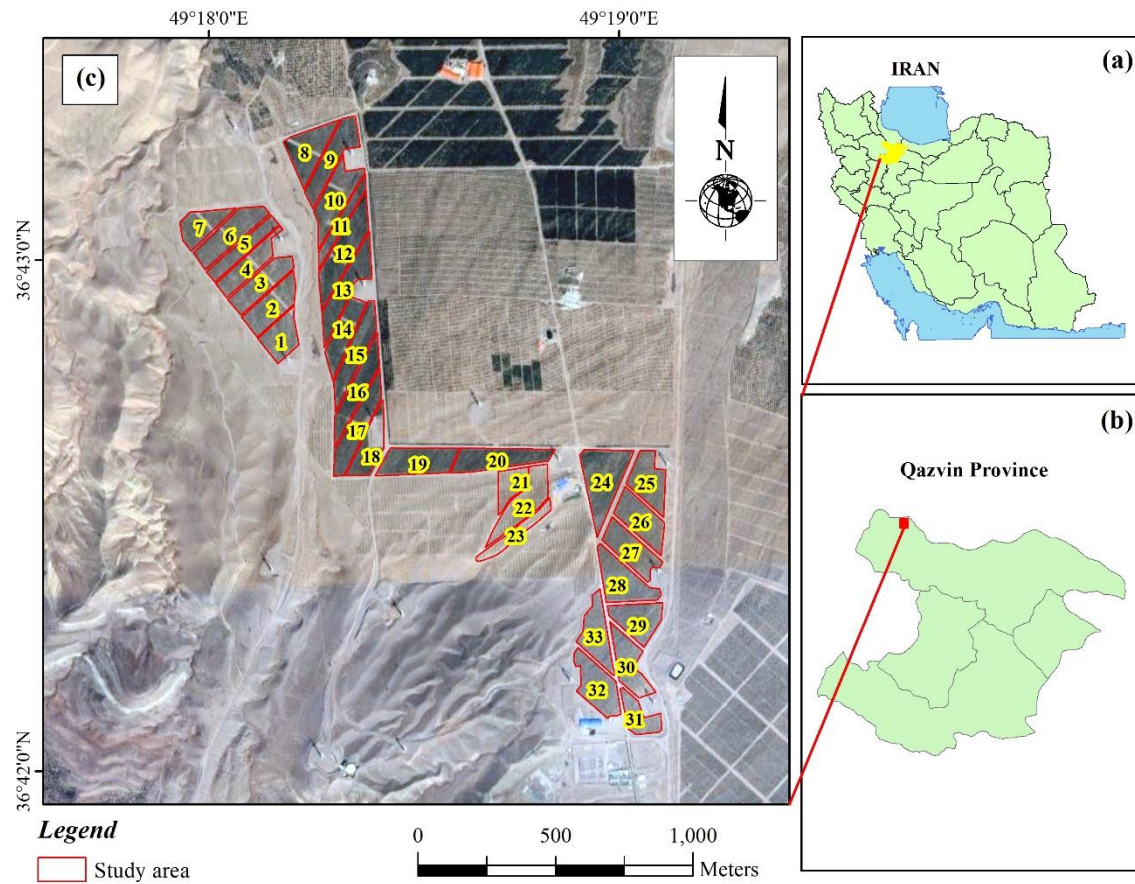


Fig. 1. Geographic location of the study area within the Tarom region (c), Qazvin Province (b), and Iran (a).

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104 2.2. Soil and irrigation water sampling and analytical procedures

Soil and irrigation water sampling was conducted in SHD olive orchards in the Tarom region. The sampling included nine orchards of the Koroneiki cultivar (orchards 1, 2, 3, 8, 9, 10, 21, 22, and 23) and twenty-four orchards of the Arbequina cultivar (Fig. 1a). All collected samples were transported to the laboratory for the determination of their physicochemical properties. Soil analyses included the measurement of soil organic matter (OM) using the Walkley–Black method¹⁴, assessment of pH¹⁵ and electrical conductivity (EC)¹⁶ in the saturated paste extract, determination of particle-size distribution (sand, silt, and clay contents) by the hydrometer method¹⁷, and quantification of sodium adsorption ratio (SAR), calcium carbonate (CCE), and gypsum (CaSO₄) using established analytical procedures¹⁸. Irrigation water samples from all orchards were also analyzed, and parameters including pH, EC, SAR, total dissolved solids (TDS), sulfate (SO₄²⁻), potassium (K⁺), sodium (Na⁺), chloride (Cl⁻), combined calcium and magnesium (Ca + Mg), carbonate (CO₃²⁻), and bicarbonate (HCO₃⁻) were determined using standard laboratory methods¹⁹.

2.3. Leaf sampling and plant nutrient analysis

Leaf sampling was conducted in mid-summer (15 July 2025) across thirty-three super-high-density (SHD) olive orchards. To ensure the results were representative of the regional soil types and management practices, orchards were selected using a random sampling approach. The study focused on seven-year-old trees of two olive cultivars: *Olea europaea* L. ‘Koroneiki’ and *Olea europaea* L. ‘Arbequina’. From five trees per orchard, a composite sample comprising 20 healthy, fully expanded leaves was collected. These leaves were harvested from the middle portion of the current season’s shoots, as this tissue is widely recognized as the most reliable indicator for evaluating the nutritional status of olive trees. To minimize bias, trees exhibiting symptoms of pests, diseases, frost damage, or severe water stress were excluded from the study.

After collection, the leaf samples were transferred to the laboratory, carefully washed with deionized water to remove dust and any external contaminants, and subsequently dried in a forced-air oven at 70 °C for 72 hours until constant weight was obtained. The dried samples were then ground using a laboratory mill to obtain a uniform powder suitable for chemical analysis.

Fruit yield was determined at harvest (25 November 2025). The total weight of olives harvested

from each sampled tree was recorded as the yield per tree, serving as a quantitative indicator of orchard productivity for correlation with nutritional status. To convert tree-level yield to a standard area-based metric (t ha⁻¹), the yield per tree was multiplied by the planting density.

The concentrations of essential macro- and micronutrients in the leaf samples were determined using established analytical procedures. Total nitrogen (N) was measured using the Kjeldahl method following wet digestion of plant tissue with concentrated sulfuric acid, after which the released nitrogen (N) was distilled and quantified²⁰. Phosphorus (P) concentration was determined spectrophotometrically after dry ashing of the plant material and subsequent color development using the ammonium molybdate–vanadate method²¹. Potassium (K) was quantified by flame photometry using extracts obtained from the ashed plant material²². Calcium (Ca) and magnesium (Mg) concentrations were determined following tissue digestion using atomic absorption spectroscopy or ethylenediaminetetraacetic acid titration procedures²³. Micronutrients including iron (Fe), zinc (Zn), copper (Cu), manganese (Mn), and boron (B) were determined after dry ashing of the samples, and their concentrations were measured using atomic absorption spectroscopy or appropriate spectrophotometric methods according to standard plant analysis protocols²⁴.

2.4. Nutrient diagnostic methods

2.4.1. Diagnosis and Recommendation Integrated System (DRIS)

The DRIS analysis involved classifying orchards into high- and low-yielding groups based on the mean yield and its standard deviation, following Sharma et al.²⁵. DRIS norms were subsequently established according to the procedure of Walworth et al.²⁶. For nutrients A through N, DRIS indices were computed as (Eq. 1):

$$\begin{aligned}
 \text{A index} &= \frac{\left[f\left(\frac{A}{B}\right) + f\left(\frac{A}{C}\right) + f\left(\frac{A}{D}\right) \cdots + f\left(\frac{A}{N}\right) \right]}{z} \\
 \text{B index} &= \frac{\left[-f\left(\frac{A}{B}\right) + f\left(\frac{B}{C}\right) + f\left(\frac{B}{D}\right) \cdots + f\left(\frac{B}{N}\right) \right]}{z} \\
 \text{C index} &= \frac{\left[-f\left(\frac{A}{C}\right) - f\left(\frac{B}{C}\right) + f\left(\frac{C}{D}\right) \cdots + f\left(\frac{C}{N}\right) \right]}{z}
 \end{aligned} \tag{1}$$

⋮

154 where, z denotes the number of ratios contributing to each index.

155 The functional terms were calculated following Beaufils²⁷ (Eq. 2):

$$\begin{aligned}
 &\text{if } \frac{A}{B} > \frac{a}{b} & f\left(\frac{A}{B}\right) &= \left(\frac{\frac{A}{B}}{\frac{a}{b}} - 1\right) \cdot \frac{1000}{CV} \\
 &\text{if } \frac{A}{B} < \frac{a}{b} & f\left(\frac{A}{B}\right) &= \left(1 - \frac{\frac{a}{b}}{\frac{A}{B}}\right) \cdot \frac{1000}{CV} \\
 &\text{if } \frac{A}{B} = \frac{a}{b} & f\left(\frac{A}{B}\right) &= 0
 \end{aligned} \tag{2}$$

156 where, A/B is the observed nutrient ratio, a/b is the corresponding DRIS norm, and CV is the
 157 coefficient of variation of the reference population.

158 The DRIS Nutrient Balance Index (NBI) was calculated as (Eq. 3):

$$NBI = |I_A| + |I_B| + |I_C| + \dots + |I_N| \tag{3}$$

159 2.4.2. Deviation from optimum percentage (DOP)

160 The DOP index quantifies the relative difference between the measured concentration of a nutrient
 161 in plant tissue and its corresponding optimal reference value. This index is calculated as follows
 162 (Eq. 4):

$$DOP = [(C \times 100) / C_{ref}] - 100 \tag{4}$$

163 where, C represents the concentration of the nutrient measured in the plant sample, and C_{ref}
 164 denotes the optimal or reference concentration for that nutrient in leaf tissue.

165 The overall nutrient imbalance can be evaluated using the DOP nutrient balance index (ΣDOP),
 166 which is obtained by summing the absolute values of the individual nutrient indices without
 167 considering their algebraic signs (Eq. 5):

$$\Sigma DOP = |I_A| + |I_B| + |I_C| + \dots + |I_N| \quad (5)$$

168 A higher ΣDOP value indicates a greater deviation from the optimal nutritional balance.

169 2.4.3. Compositional Nutrient Diagnosis (CND)

170 The CND approach was introduced by Parent and Dafir²⁸. This method treats plant nutrient
171 composition as a multivariate system in which the sum of all nutrient concentrations equals a
172 constant value. In this framework, the total nutrient concentration in plant tissue is assumed to be
173 100%, while the remaining portion is represented by a residual component denoted as R_d . The
174 number of nutrients included in the analysis is represented by d .

175 The compositional structure of plant nutrients can therefore be expressed as (Eq. 6):

$$100S_d = [(N, P, K, \dots, R_d) \ N > 0, P > 0, K > 0, \dots, R_d > 0] \ N + P + K + \dots + R_d = 1 \quad (6)$$

176 The residual component is calculated as (Eq. 7):

$$R_d = 100 - (N + P + K \dots) \quad (7)$$

177 To separate orchards into high-yielding and low-yielding groups, observations are first ranked
178 according to yield values²⁹. Subsequently, the geometric mean of nutrient concentrations is
179 calculated (Eq. 8):

$$G = [N, P, K, \dots, R_d]^{\frac{1}{d+1}} \quad (8)$$

180 Next, centered log ratios are obtained by comparing each nutrient concentration with the geometric
181 mean (Eq. 8):

$$V_N = \ln\left(\frac{N}{G}\right), V_P = \ln\left(\frac{P}{G}\right), V_K = \ln\left(\frac{K}{G}\right), \dots, V_{R_d} = \ln\left(\frac{R_d}{G}\right) \quad (9)$$

182 The sum of all logarithmic ratios must equal zero, confirming the correctness of the compositional
183 transformation (Eqs. 10-11):

$$V_N + V_P + V_K + \dots + V_{Rd} = 0 \quad (10)$$

$$F_i = \frac{\sum_{i=1}^{n-1} f_i(v_X)}{\sum_{i=1}^{n-3} f_i(v_X)} \times 100 \quad (11)$$

184 The cumulative variance ratio function (Fic(Vx)) is then determined for each nutrient variable.
 185 The relationship between Fic(Vx) and yield is described using a third-order polynomial model.
 186 The mean inflection point of these curves, calculated as $(-b/3a)$, represents the midpoint separating
 187 low- and high-yielding populations and helps identify the optimal nutrient balance associated with
 188 maximum yield.

189 For nutrient balance assessment, CND indices are calculated by standardizing each logarithmic
 190 ratio relative to its corresponding reference norm. For instance, the indices for N, P, K, and the
 191 residual component (Rd) are determined as (Eq. 12):

$$\begin{aligned} I_N &= \frac{V_N - V_N^*}{SD_{Rd}^*} \\ I_P &= \frac{V_P - V_P^*}{SD_{Rd}^*} \\ I_K &= \frac{V_K - V_K^*}{SD_{Rd}^*} \\ &\dots, \\ I_{Rd} &= \frac{V_{Rd} - V_{Rd}^*}{SD_{Rd}^*} \end{aligned} \quad (12)$$

192 where, V^* represents the mean value of the logarithmic ratios obtained from the reference
 193 population, and SD^* indicates their corresponding standard deviations.

194 The nutrient balance index is finally computed as the sum of the squared nutrient indices (Eq. 13):

$$r^2 = I_N^2 + I_P^2 + I_K^2 + \dots + I_{Rd}^2 \quad (13)$$

where, values of r^2 closer to zero indicate a more balanced nutrient composition within plant tissues.

2.5. NDVI data set

To assess vegetation vigor in the study areas, satellite remote sensing techniques were employed. In this study, multispectral images from the Sentinel-2 satellite of the Copernicus program (European Space Agency) were used. Sentinel-2 provides high spatial resolution imagery (10–20 m) with several spectral bands in the visible and near-infrared regions, making it suitable for monitoring vegetation conditions and agricultural landscapes. Vegetation greenness was quantified using the normalized difference vegetation index (NDVI), one of the most widely used spectral indices in remote sensing for evaluating vegetation density and health. NDVI is calculated based on the contrast between the strong absorption of red light by chlorophyll and the high reflectance of near-infrared radiation by plant canopies. The NDVI was calculated using the following equation (Eq. 14):

$$NDVI = (NIR - Red)/(NIR + Red) \quad (14)$$

where, NIR represents the reflectance in the near-infrared band and Red represents the reflectance in the red band of the electromagnetic spectrum. NDVI values typically range from -1 to $+1$, where higher positive values indicate dense and healthy vegetation, while values close to zero or negative represent non-vegetated surfaces such as bare soil, water bodies, or built-up areas³⁰.

In this study, Sentinel-2 imagery corresponding to the crop growing period was processed using the Google Earth Engine (<https://code.earthengine.google.com/>) platform. Cloud-affected pixels were filtered to ensure image quality, and NDVI maps were generated for the study area. The resulting NDVI layers were then exported and further processed in ENVI 5.8 to extract NDVI values for the sampling locations and to prepare the final spatial datasets used in subsequent analyses.

2.6. Statistical analyses

Correlations among nutrient concentrations, physiological indices (DOP, DRIS, CND, and NBI), and crop yield with NDVI were analyzed using the `corrplot` package in R (version 4.2.2).

3. Results

3.1. Soil physicochemical properties

Fig. 2 and Table 1 together describe the distribution and quantitative behavior of the major soil physicochemical properties observed under the SHD olive cultivation system. Soil pH exhibited a relatively narrow numerical range (7.4–8.1), with a mean and median of 7.7 and a standard deviation (SD) of 0.18, indicating limited dispersion around moderately alkaline conditions. EC demonstrated broader variability, ranging from 1.12 to 3.36 dS m⁻¹ (mean = 2.25; SD = 0.64), as reflected in an interquartile interval extending from 1.89 to 2.76 dS m⁻¹. The SAR showed the widest spread among the chemical indicators, with values between 5.40 and 12.6 (mean = 9.58; SD = 2.07) and quartiles spanning 7.80–11.2, highlighting considerable heterogeneity in sodicity-related conditions. The CCE content ranged from 7.0% to 14.0%, with a mean of 10.4% and an interquartile range of 9.0–11.5%, while CaSO₄ concentrations varied from 0.32% to 1.70% (mean = 0.68%; SD = 0.35), clustering primarily within the 0.42–0.76% interval but with a few higher observations expanding the overall distribution.

OM levels were consistently low throughout the study area, ranging from 0.11% to 0.61% (mean = 0.312%; SD = 0.11), with quartile boundaries of 0.21% and 0.40%, indicating uneven spatial distribution. Textural data revealed that soils were predominantly sandy, with sand content ranging from 55% to 88% (mean = 75%; SD = 9.04), accompanied by comparatively lower proportions of silt (6–31%; mean = 16%; SD = 6.17) and clay (2–18%; mean = 8%; SD = 4.02). The respective interquartile ranges for sand (70–80%), silt (12–20%), and clay (6–10%) reflect measurable spatial variation in particle-size distribution across sampling locations. Collectively, the statistical distribution patterns depicted in Fig. 2 and Table 1 illustrate substantial variability across salinity indicators (EC, SAR), CCE and gypsum contents, OM levels, and textural fractions. These data characterize a heterogeneous soil environment within the SHD olive system, with notable differences in chemical and physical properties across the sampled sites.

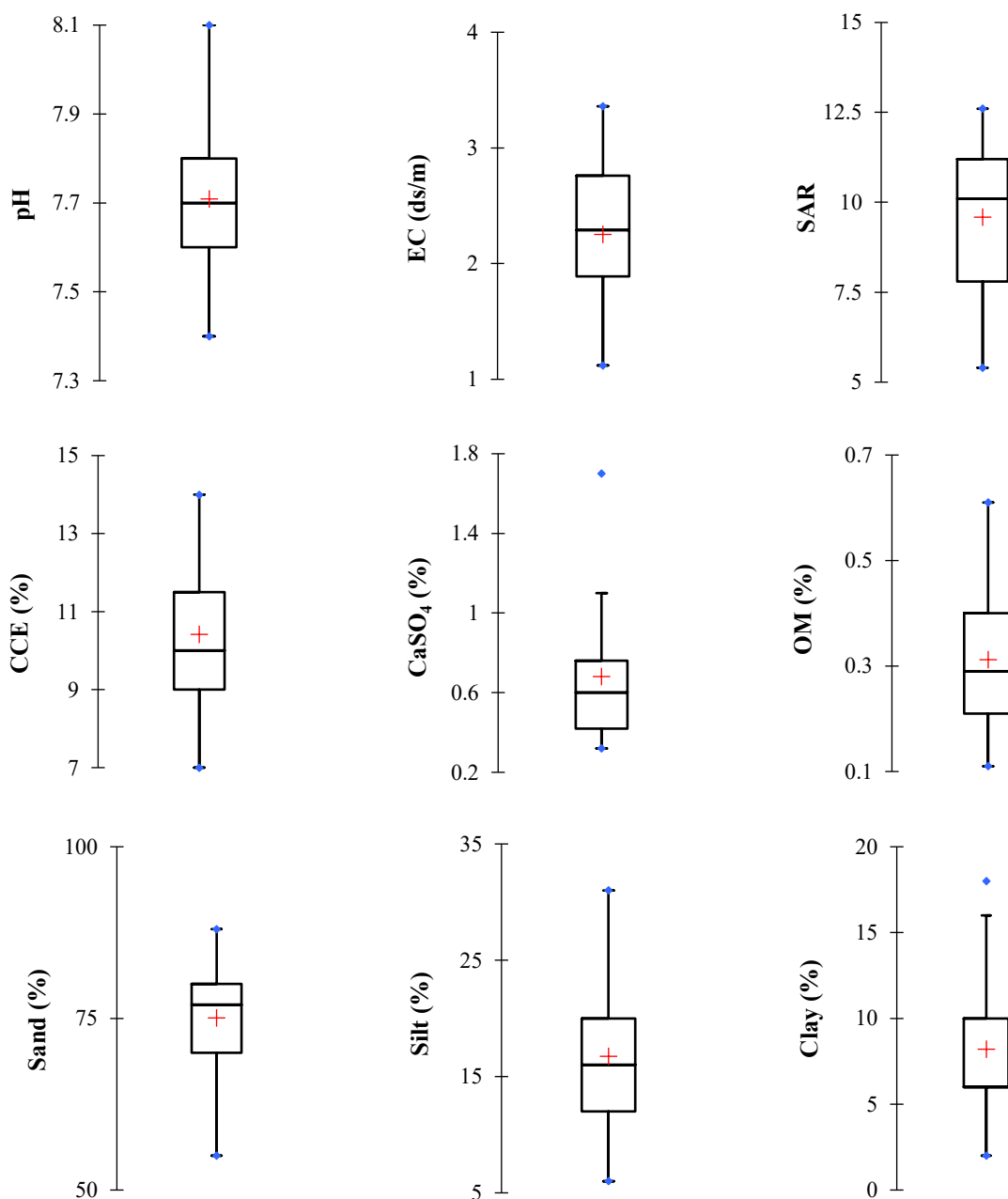


Fig. 2. Box plots illustrating key soil physicochemical properties, including pH, elect EC (dS/m), SAR, CCE (%), CaSO₄ (%), OM (%), and soil texture.

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Table 1. Descriptive statistics of soil properties under olive SHD system cultivation.

Statistic	pH	EC (ds/m)	SAR	CaSO ₄ (%)	CCE (%)	OM (%)	Sand %	Silt %	Clay %
Minimum	7.4	1.12	5.40	0.32	7.0	0.11	55	6	2
Maximum	8.1	3.36	12.6	1.70	14.0	0.61	88	31	18
1st Quartile	7.6	1.89	7.80	0.42	9.0	0.21	70	12	6

Median	7.7	2.29	10.1	0.60	10.0	0.29	77	16	6
3rd Quartile	7.8	2.76	11.2	0.76	11.5	0.40	80	20	10
Mean	7.7	2.25	9.58	0.68	10.4	0.31	75	16	8
Variance	0.03	0.42	4.32	0.12	3.11	0.01	81.7	38.1	16.2
Standard deviation	0.18	0.64	2.07	0.35	1.76	0.11	9.04	6.17	4.02

3.2. Characteristics of irrigation water

Table 2 summarizes the measured chemical properties of the irrigation water used in the studied SHD olive orchards. The EC of the water was recorded at $4,960 \mu\text{S cm}^{-1}$, while TDS reached $3,174 \text{ mg L}^{-1}$. The measured pH value was 7.65. The concentrations of the principal cations and anions were also determined. Sodium concentration was 23.98 mg L^{-1} , whereas the combined concentration of Ca and Mg reached 34.50 mg L^{-1} . Chloride and sulfate were present at 33.88 mg L^{-1} and 23.0 mg L^{-1} , respectively. Additional dissolved constituents included bicarbonate with a concentration of 1.40 mg L^{-1} and carbonate with a value of 0.34 mg L^{-1} . The dataset also includes measurements of other ions and indices describing the ionic composition of the irrigation water. Potassium concentration was measured at 0.12 mg L^{-1} . In addition, the SAR was calculated as 5.77.

Table 2. Physicochemical parameters of irrigation water in the investigated area.

Water Sample	pH	EC	CO ₃	HCO ₃	Cl	Ca+Mg	Na	K	SO ₄	TDS	SAR
		($\mu\text{S/m}$)				(mEq/L)				(mg/L)	
	7.65	4960	0.34	1.40	33.88	34.50	23.98	0.12	23.0	3174	5.77

Fig. 3 illustrates the monthly variation of EC and pH in irrigation water during the year 2025. In Fig. 3a, EC values show monthly fluctuations over the monitoring period. The recorded EC values ranged approximately from 1.7 to 3.4 dS m^{-1} . Lower EC values were observed during the early months of the year, followed by gradual changes during the spring months. Higher EC values appeared during the summer period, with the maximum level occurring around September. After this point, EC values slightly decreased but remained within a relatively elevated range toward the end of the year. Fig. 3b presents the monthly changes in pH of the irrigation water. The pH values varied within a relatively narrow range, approximately between 7.5 and 8.4 during the monitoring period. Monthly fluctuations were observed throughout the year, with lower values recorded in

some winter and early summer months, while relatively higher values appeared in mid-summer and again toward the end of the year.

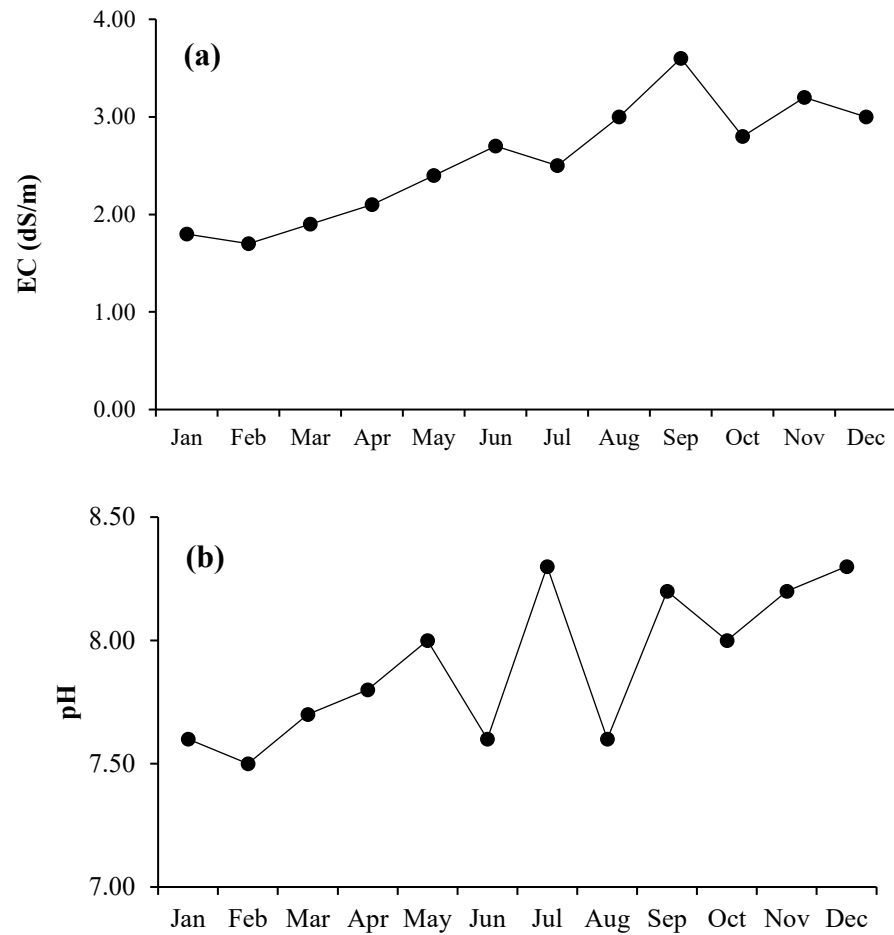


Fig. 3. EC (a) and pH (b) of irrigation water in the study area in 2025.

3.3. DRIS, DOP, and CND methods

3.3.1. Selection of High-Yielding Community and determination of norms

Based on the procedure described by Sharma et al.²⁵, the average yield of the evaluated SHD olive orchards was calculated as 16.14 t ha⁻¹ and used as the reference value for separating the dataset into high- and low-yielding groups for the DRIS and DOP analyses. Using this method, the orchards were categorized into two productivity classes. Five orchards, representing approximately 15% of the total sampled population, were classified in the high-yield group, whereas the remaining twenty-eight orchards (about 85%) were assigned to the low-yield category.

The mean yield values recorded for these groups were 17.3 t ha⁻¹ for the high-yield orchards and

12.4 t ha⁻¹ for the low-yield orchards (Table 3).

The statistical characteristics of leaf nutrient concentrations for the two productivity groups are presented in Table 3, including mean values, SD, variance (S²), and coefficient of variation (CV). In the low-yield group, the average concentrations were 2.32% N, 0.16% P, 1.14% K, 2.09% Ca, and 0.14% Mg, while micronutrient concentrations were 0.035% Fe, 0.004% Mn, 0.002% Zn, 0.001% Cu, and 0.020% B. In the high-yield orchards, the corresponding mean concentrations were 2.28% N, 0.18% P, 1.18% K, 2.23% Ca, and 0.13% Mg, with micronutrient levels of 0.035% Fe, approximately 0.004% Mn, 0.003% Zn, 0.002% Cu, and 0.023% B. The calculated coefficients of variation showed differences among nutrients and between yield groups, indicating variability in nutrient concentrations within the evaluated orchards.

Table 3. Statistical parameters of high- and low-yielding groups derived using the DRIS and DOP approaches.

Olive orchards		Yield	N%	P%	K%	Ca%	Mg%	Fe%	Mn%	Zn%	Cu%	B%
Low-yielding	Mean	12.4	2.32	0.16	1.14	2.09	0.14	0.035	0.004	0.002	0.001	0.020
	SD	2.53	0.09	0.03	0.12	0.21	0.02	0.02	0.00	0.00	0.00	0.01
	S ²	6.38	0.01	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.00
	CV	20.2	3.8	17.6	10.6	10.2	12.4	55.28	13.46	24.21	33.80	41.63
High-yielding	Mean	17.3	2.28	0.18	1.18	2.23	0.13	0.035	0.004	0.003	0.002	0.023
	SD	1.01	0.13	0.02	0.11	0.50	0.01	0.02	0.00	0.00	0.00	0.01
	S ²	1.03	0.02	0.00	0.01	0.25	0.00	0.00	0.00	0.00	0.00	0.00
	CV	5.84	5.57	11.6	9.13	22.2	8.60	66.75	25.59	16.61	116.8	47.07

Based on the comparison of variances between the low- and high-yielding groups, nutrient ratios with a higher SB/SA value were selected as DRIS norms, resulting in the identification of 45 ratios for the high-yielding orchards (Table 4). These ratios include combinations of macronutrients and micronutrients such as P/N, K/N, Ca/N, N/Mg, N/Fe, N/Mn, Zn/N, Cu/N, and B/N, as well as reciprocal and cross-element ratios. For each selected ratio, Table 4 reports the mean value and the corresponding CV, which varied widely depending on the nutrient pair. Ratios such as Cu/B, Cu/Ca, and Cu/Zn showed the highest CV values, whereas ratios like K/Mg, N/Mg, and K/N exhibited relatively low variability within the high-yielding group. All listed ratios constitute the DRIS norms used for subsequent diagnostic calculations.

Table 4. Nutrient ratio DRIS norms and their CV in high-yielding orchards.

Norm	Mean	CV (%)	Norm	Mean	CV (%)	Norm	Mean	CV (%)
P/N	0.08	6.98	Cu/P	0.01	109.44	Mg/Fe	5.47	65.45
K/N	0.52	5.3	P/B	9.54	53.30	Mg/Mn	34.4	27.22
Ca/N	0.99	28.82	Ca/K	1.93	29.5	Zn/Mg	0.02	19.55
N/Mg	17.2	4.46	K/Mg	8.88	3.79	Cu/Mg	0.02	106.91
N/Fe	94.8	65.11	K/Fe	48.2	63.08	B/Mg	0.176	46.66
N/Mn	591.5	26.46	K/Mn	303.4	23.8	Fe/Mn	8.21	54.21
Zn/N	0.00	19.23	Zn/K	0.00	20.76	Zn/Fe	0.11	57.22
Cu/N	0.00	111.68	Cu/K	0.00	104.39	Cu/Fe	0.07	53.99
B/N	0.01	47.67	K/B	62.5	56.7	B/Fe	1.13	106.65
P/K	0.15	9.32	Ca/Mg	17.1	30.95	Zn/Mn	0.73	29.12
Ca/P	12.7	37.9	Ca/Fe	94.2	65.95	Cu/Mn	0.53	86.93
P/Mg	1.37	7.58	Ca/Mn	586.7	35.55	B/Mn	6.61	74.33
P/Fe	7.6	67.84	Zn/Ca	0.00	18.87	Cu/Zn	0.92	121.22
P/Mn	47.3	29.39	Cu/Ca	0.00	131.26	B/Zn	8.33	51.49
Zn/P	0.02	23.74	B/Ca	0.01	44.85	Cu/B	0.17	159.13

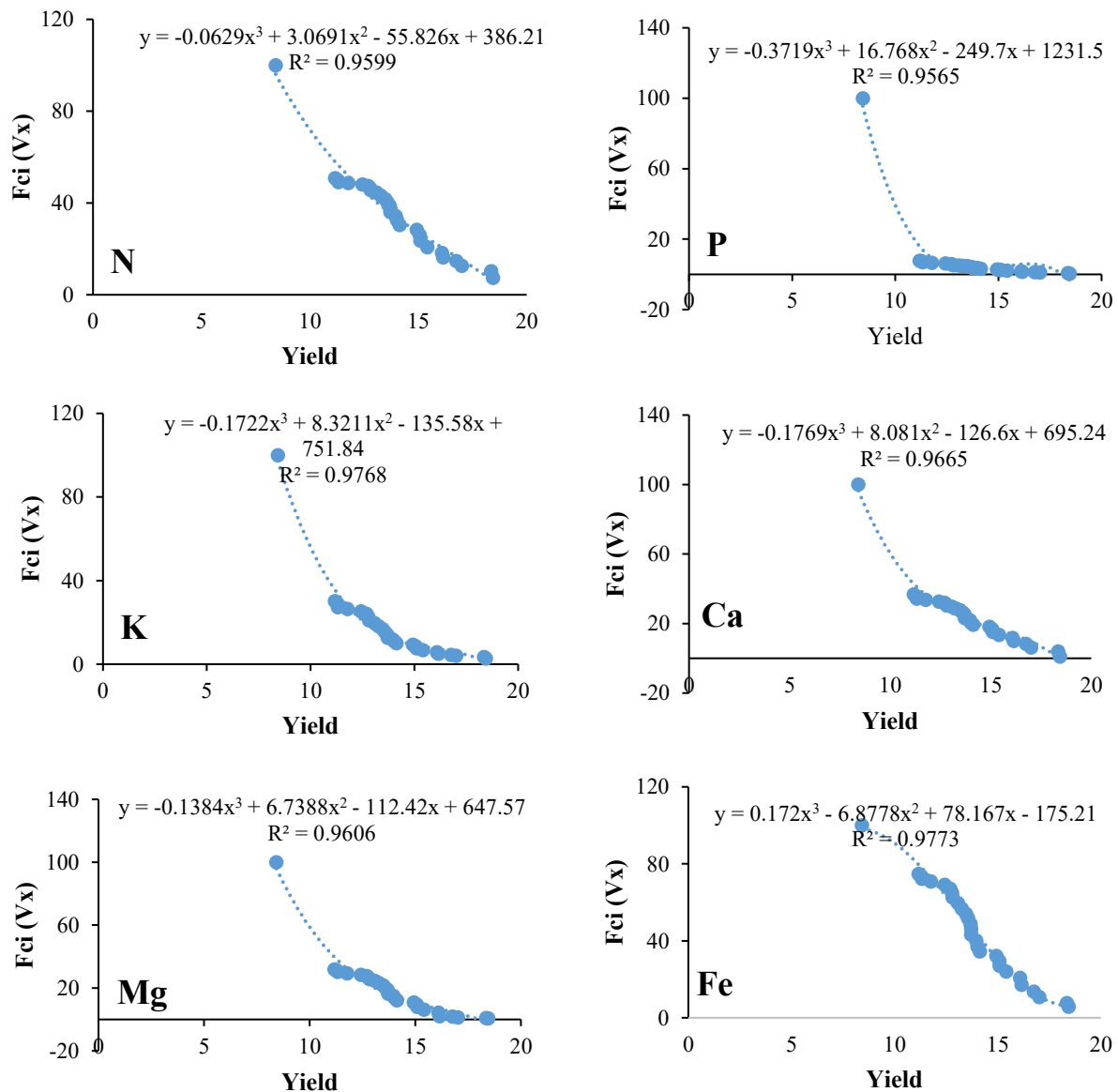
In addition to the DRIS norms, the mean nutrient concentrations of the high-yielding orchards were used to establish the DOP norms (Table 5). The average macronutrient concentrations were 2.28% N, 0.18% P, 1.18% K, 2.23% Ca, and 0.13% Mg. The corresponding micronutrient concentrations included 351 ppm Fe, 41 ppm Mn, 28 ppm Zn, 24 ppm Cu, and 231 ppm B, representing the mean values calculated from the high-yielding population. These measurements form the DOP reference set and were used directly as the standard nutrient levels for the subsequent DOP-based nutrient diagnosis.

Table 5. Mean nutrient concentrations in high-yielding olive trees used as DOP norms.

Nutrient	N %	P %	K %	Ca %	Mg %	Fe (ppm)	Mn (ppm)	Zn (ppm)	Cu (ppm)	B (ppm)
Norm	2.28	0.18	1.18	2.23	0.13	351	41	28	24	231

As illustrated in Fig. 4, the relationship between Fic (VX) values and yield for each nutrient was modeled using third-degree polynomial functions, all of which showed a decreasing trend in Fic(VX) with increasing yield and exhibited strong coefficients of determination, generally above 0.95 and within the overall range of 0.89 to 0.99. Building on the functions presented in Fig. 4, the corresponding yield turning points ($-b/3a$) calculated from these polynomial models are summarized in Table 6. The turning points varied among nutrients, with values of 16.26 for N,

315 15.03 for P, 16.11 for K, 15.23 for Ca, 16.23 for Mg, 13.33 for Fe, 10.36 for Mn, 17.17 for Zn,
 316 30.84 for Cu, and 13.85 for B. The reference diagnostic variable (Rd) showed a turning point of
 317 14.80, while its residual component (V*Rd) reached 6.53 with a standard deviation of 0.12,
 318 representing the highest positive value among the evaluated variables. Based on an intermediate
 319 yield threshold of 16.19 t ha⁻¹, orchards were grouped into two CND performance categories, with
 320 12% of orchards (four orchards) classified as high-yielding and 88% (twenty-nine orchards) as
 321 low-yielding.



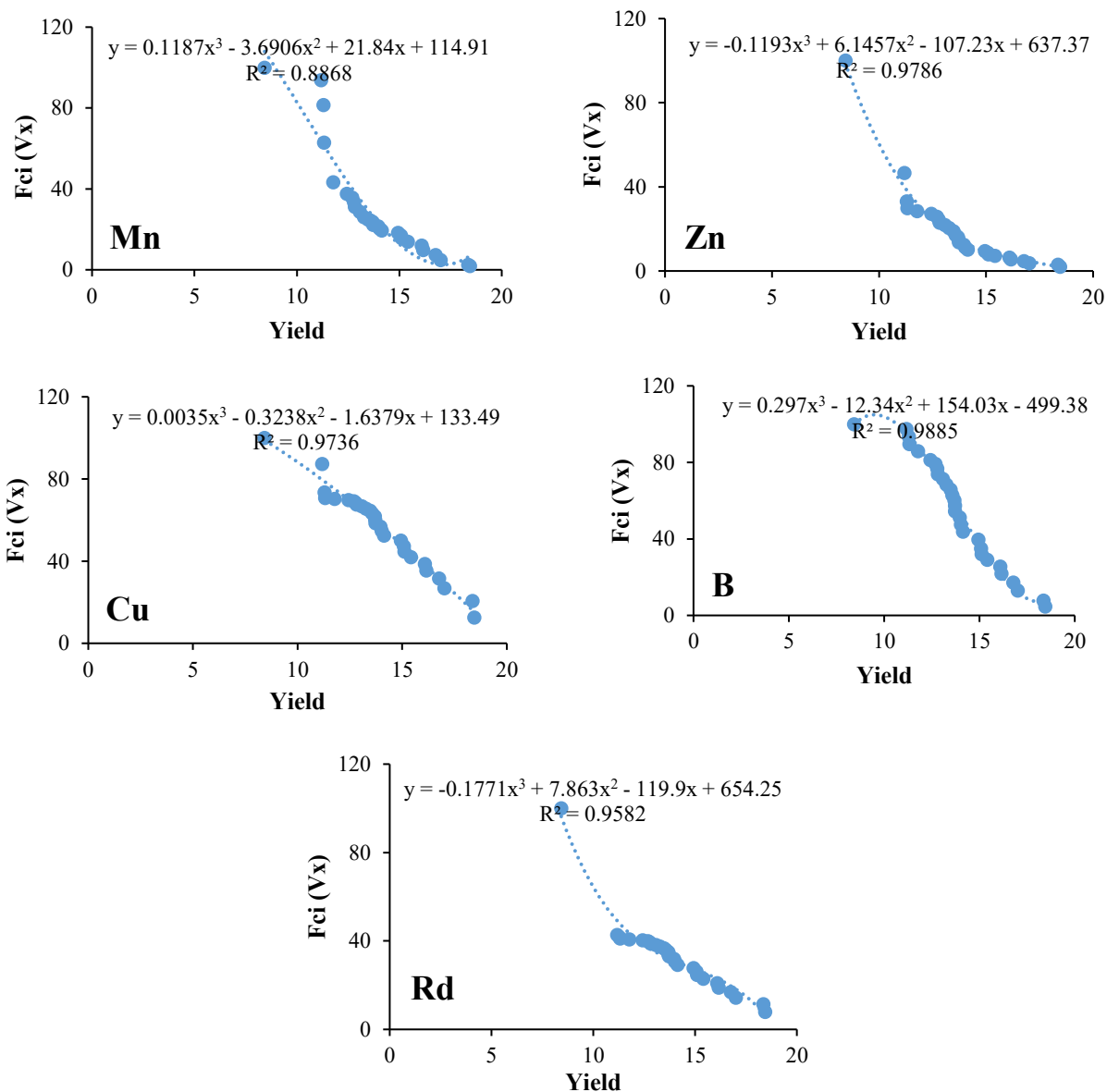


Fig. 4. Cumulative variance ratio functions obtained from yield-driven analysis of macro- and micronutrient variables.

322

Table 6. Yield turning points ($-b/3a$) used to identify the high-yielding group and establish CND norms.

Nutrients	a	b	$-b/3a$	V^*x	SD^*	R^2
N	-0.0629	3.069	16.26	2.82	0.116	0.96
P	-0.3719	16.768	15.03	0.28	0.167	0.96
K	-0.1722	8.3211	16.11	2.16	0.083	0.98
Ca	-0.1769	8.081	15.23	2.77	0.295	0.97
Mg	-0.1384	6.7388	16.23	-0.03	0.082	0.96
Fe	0.172	-6.8778	13.33	-1.34	0.490	0.98

Mn	0.1187	-3.6906	10.36	-3.44	0.121	0.89
Zn	-0.1193	6.1457	17.17	-3.87	0.188	0.98
Cu	0.0035	-0.3238	30.84	-4.30	0.866	0.97
B	0.297	-12.34	13.85	-2.02	0.432	0.99
Rd	-0.1771	7.863	14.80	6.53	0.126	0.96

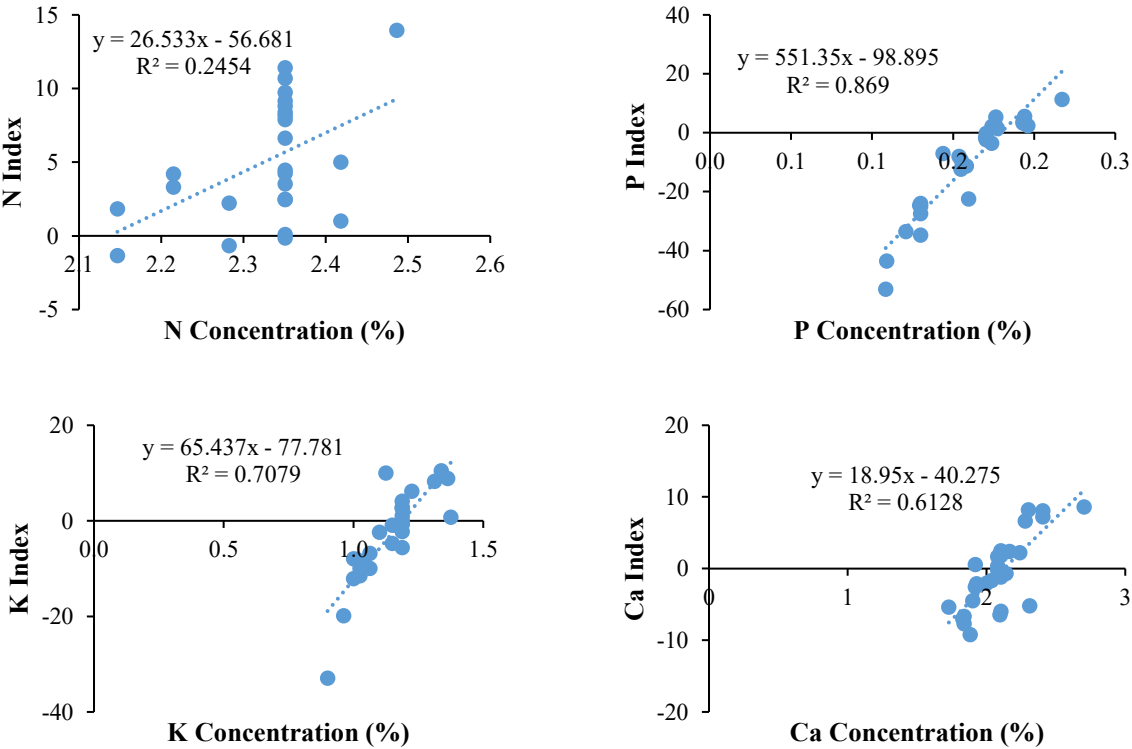
The nutrient norms used in the CND method were derived from the mean nutrient concentrations of orchards classified as high yielding, and the descriptive statistics for both productivity groups are presented in Table 7. In the high-yielding orchards, the average concentrations of macronutrients were 2.28% N, 0.18% P, 1.19% K, 2.23% Ca, and 0.13% Mg, whereas the corresponding values for the low-yielding orchards were 2.32% N, 0.16% P, 1.14% K, 2.10% Ca, and 0.14% Mg. With respect to micronutrients, the high-yielding group showed mean concentrations of 407.5 ppm Fe, 44.03 ppm Mn, 28.75 ppm Zn, 27.64 ppm Cu, and 0.02 ppm B. In comparison, the low-yielding orchards exhibited mean values of 341.9 ppm Fe, 43.06 ppm Mn, 23.40 ppm Zn, 13.37 ppm Cu, and 0.02 ppm B. Yield performance also differed between the two groups, with an average of 17.65 t ha⁻¹ recorded for the high-yielding orchards and 12.57 t ha⁻¹ for the low-yielding orchards. These statistical characteristics provided the quantitative basis for establishing the CND norms applied in the subsequent nutrient diagnostic analysis.

Table 7. Descriptive statistics of nutrient concentrations and yield for low- and high-yielding orchard groups obtained using the CND approach.

Nutrients (%)	Low-yielding groups			High -yielding groups		
	Mean	SD	CV (%)	Mean	SD	CV (%)
N	2.32	0.09	3.79	2.28	0.15	6.43
P	0.16	0.03	17.48	0.18	0.02	13.48
K	1.14	0.12	10.48	1.19	0.12	10.35
Ca	2.10	0.21	10.12	2.23	0.58	25.74
Mg	0.14	0.02	12.31	0.13	0.01	9.92
Fe	341.9	194.4	56.86	407.5	227.3	55.79
Mn	43.06	6.55	15.21	44.03	8.14	18.48
Zn	23.40	5.56	23.76	28.75	5.10	17.75
Cu	13.37	4.47	33.43	27.64	31.93	115.56
B	0.02	0.01	43.10	0.02	0.01	33.97
Yield	12.57	2.57	20.47	17.65	0.88	5.00

3.3.2. Nutrients indices

338 Nutrient diagnostic indices were computed using the DRIS, DOP, and CND approaches based on
 339 the reference population of high-yielding olive SHD orchards. The nutrient concentrations
 340 measured in the high-yielding subpopulation were used as the reference norms for index
 341 calculations. Comparison of nutrient concentrations between the high-yielding reference orchards
 342 and the remaining orchards revealed statistically distinguishable differences between the two
 343 productivity groups. The associations between DRIS indices and corresponding nutrient
 344 concentrations are illustrated in Fig. 5. Scatter plots show the distribution of nutrient indices
 345 relative to measured concentrations for N, P, K, Ca, Mg, Fe, Mn, Zn, Cu, and B. Linear regression
 346 models were fitted for each nutrient, and the equations together with the coefficients of
 347 determination (R^2) are presented in the respective panels. Across the evaluated nutrients, DRIS
 348 indices varied across both negative and positive ranges around the zero reference line, while the
 349 observed data points followed the fitted linear trends between nutrient concentration and the
 350 corresponding DRIS index values.



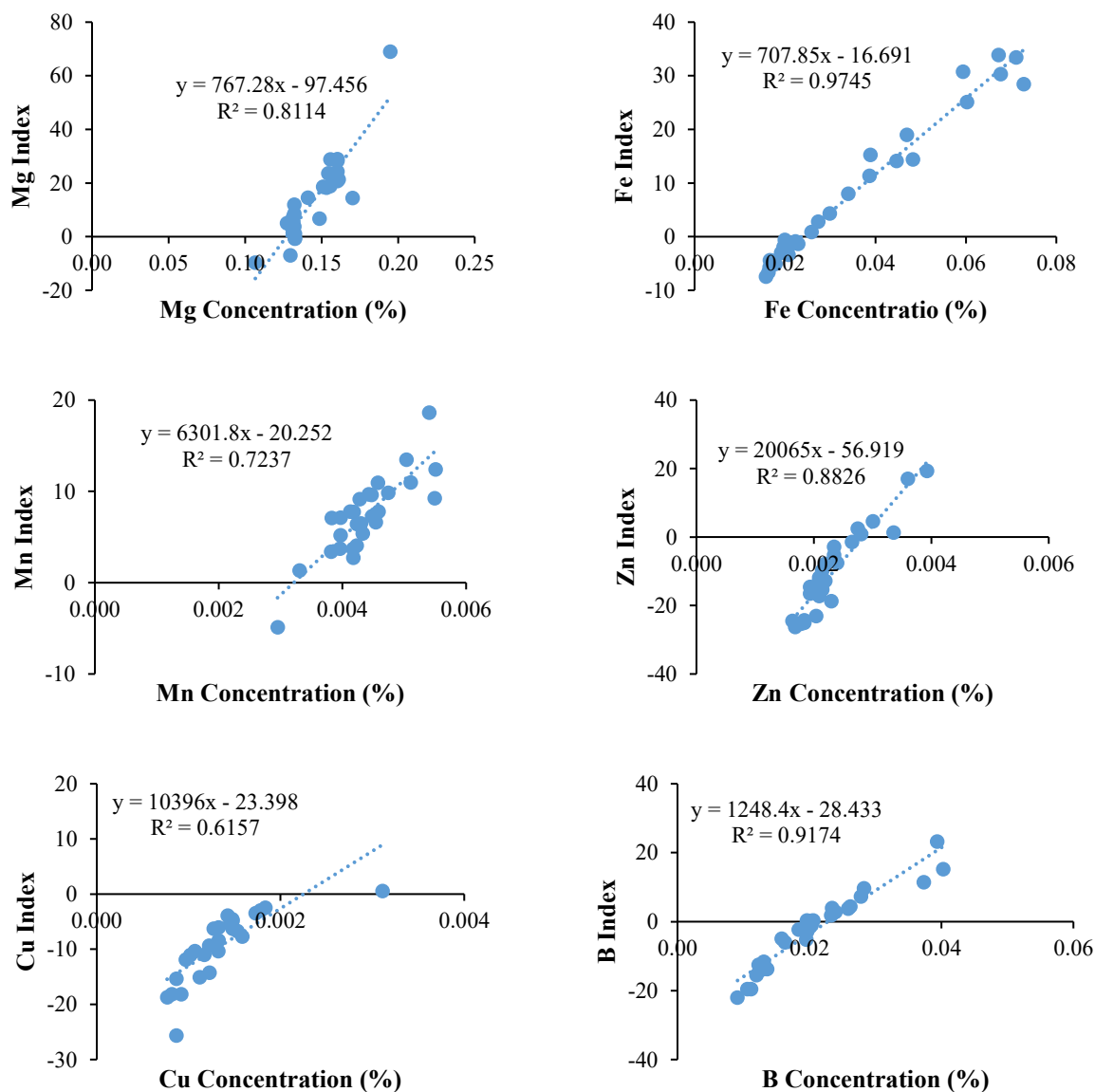


Fig. 5. Relationship between DRIS indices and nutrient concentrations.

351 The mean nutrient indices derived from the DRIS, DOP, and CND diagnostic systems are
 352 summarized in Table 8 along with the corresponding nutrient-requirement ranking for
 353 low-yielding orchards. Among macronutrients, the DRIS indices showed negative values for P
 354 (−10.99) and K (−3.23), while DOP produced similar negative values for these elements (−11.42
 355 and −3.45, respectively). The CND indices also showed negative values for P (−0.37) and a slightly
 356 positive value for K (0.30). Nitrogen indices across the three methods were consistently positive,
 357 with values of 4.99, 1.92, and 0.74. Calcium and Mg exhibited positive indices in all diagnostic

systems, with Mg showing the highest positive values among macronutrients (13.29 for DRIS, 11.04 for DOP, and 1.82 for CND). The macronutrient demand ranking reported by all three methods followed the same sequence: P > K > N > Ca > Mg.

For micronutrients, the DRIS indices indicated negative values for Zn (−10.12), Cu (−9.43), and B (−2.87), whereas Fe and Mn yielded positive values of 7.24 and 8.06, respectively. DOP indices showed the lowest values for Cu (−44.05) and Zn (−16.70), followed by B (−11.37), while Fe (−0.37) and Mn (6.43) showed contrasting signs. The CND indices also presented negative values for Zn (−0.80), Cu (−0.34), and Fe (−0.25), while Mn and B were slightly positive at 0.37 and 0.32. Based on these indices, the micronutrient-need order varied slightly among the methods: Zn > Cu > B > Fe > Mn (DRIS), Cu > Zn > B > Fe > Mn (DOP), and Zn > Cu > Fe > B > Mn (CND). Table 8 also shows that, despite methodological differences among DRIS, DOP, and CND, the productivity-based classification of low-yielding orchards resulted in similar nutrient-need categorizations across the three diagnostic systems.

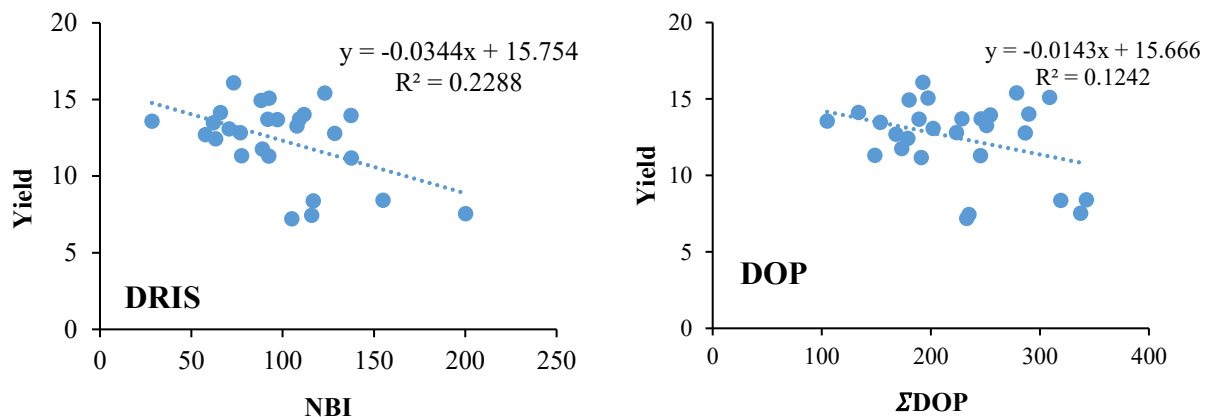
Table 8. Mean of nutrient indices and corresponding order of nutrient requirement.

Mean	DRIS	DOP	CND
I _N	4.99	1.92	0.74
I _P	-10.99	-11.42	-0.37
I _K	-3.23	-3.45	0.30
I _{Ca}	6.60	6.26	0.75
I _{Mg}	13.29	11.04	1.82
I _{Fe}	7.24	-0.37	-0.25
I _{Mn}	8.06	6.43	0.37
I _{Zn}	-10.12	-16.70	-0.80
I _{cu}	-9.43	-44.05	-0.34
I _B	-2.87	-11.37	0.32
Macro nutrients	P>K>N>Ca>Mg	P>K>N>Ca>Mg	P>K>N>Ca>Mg
Micro nutrients	Zn>Cu>B>Fe>Mn	Cu>Zn>B>Fe>Mn	Zn>Cu>Fe>B>Mn

3.3.3. Nutritional balance index

The NBI, Σ DOP, and r^2 values derived from the DRIS, DOP, and CND diagnostic approaches are

375 shown in Fig. 6. In low-yielding olive SHD orchards, the computed NBI ranged
 376 between 28.4 and 200.2, Σ DOP varied from 104.9 to 342.5, and CND-based r^2 values extended
 377 from 2.8 to 35.9. The graphical plots demonstrate the quantitative associations between yield and
 378 the corresponding nutritional balance parameters for each diagnostic method. Regression fitting
 379 yielded negative linear relationships represented by $y = -$
 380 $0.0344x + 15.754$ ($R^2 = 0.2288$) for DRIS, $y = -0.0143x + 15.666$ ($R^2 = 0.1242$) for DOP, and $y = -$
 381 $0.1243x + 14.416$ ($R^2 = 0.1936$) for CND, as indicated in Fig. 6. All three methods exhibited
 382 declining trends of yield with increasing nutrient balance indices. Across evaluated orchards, the
 383 lower NBI, Σ DOP, and r^2 values were recorded in leaves exhibiting relatively uniform elemental
 384 compositions, whereas higher index values occurred under broader elemental deviations. The
 385 numerical dispersion observed in Fig. 6 reflects the variability of nutrient balance conditions
 386 among the studied low-yielding plots. Table 8 and Fig. 6 together clarify the magnitude range of
 387 nutrient imbalance quantified by DRIS, DOP, and CND diagnostics under the SHD olive orchard
 388 framework.



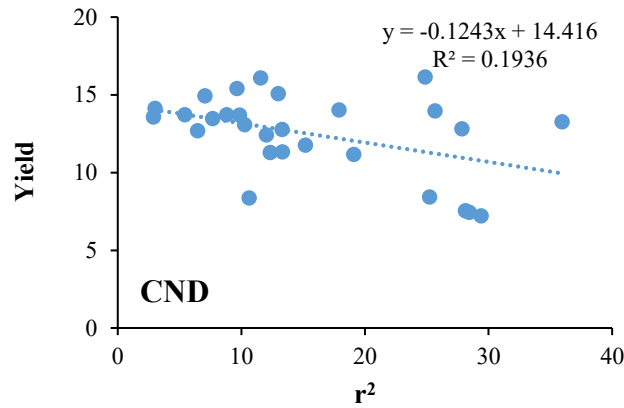


Fig. 6. Relationship between the nutrient balance indices derived from DRIS, DOP, and CND and the yield of olive SHD orchards.

3.4. NDVI and its seasonal variability

Fig. 7 displays the processed NDVI map for the 33 olive orchards, generated following pixel-based computation over the selected imagery dates. The color-coded map represents the spatial gradients of NDVI, where each orchard block is classified according to the relative index values derived from the satellite observations. Across the mapped area, NDVI values ranged from 0.39 to 0.115, corresponding to the highest and lowest index classes, respectively, as shown in Fig. 7. The spatial distribution of NDVI is illustrated through a continuous color scale, with green-to-blue hues indicating the upper range of the observed values and yellow-to-red hues identifying the lower range. The polygonal boundaries delineate the orchard blocks included in the analysis, providing an overview of within-orchard variability captured by the remote-sensing data. The map presented in Fig. 7 summarizes the final NDVI classification applied to all orchard units included in the study.

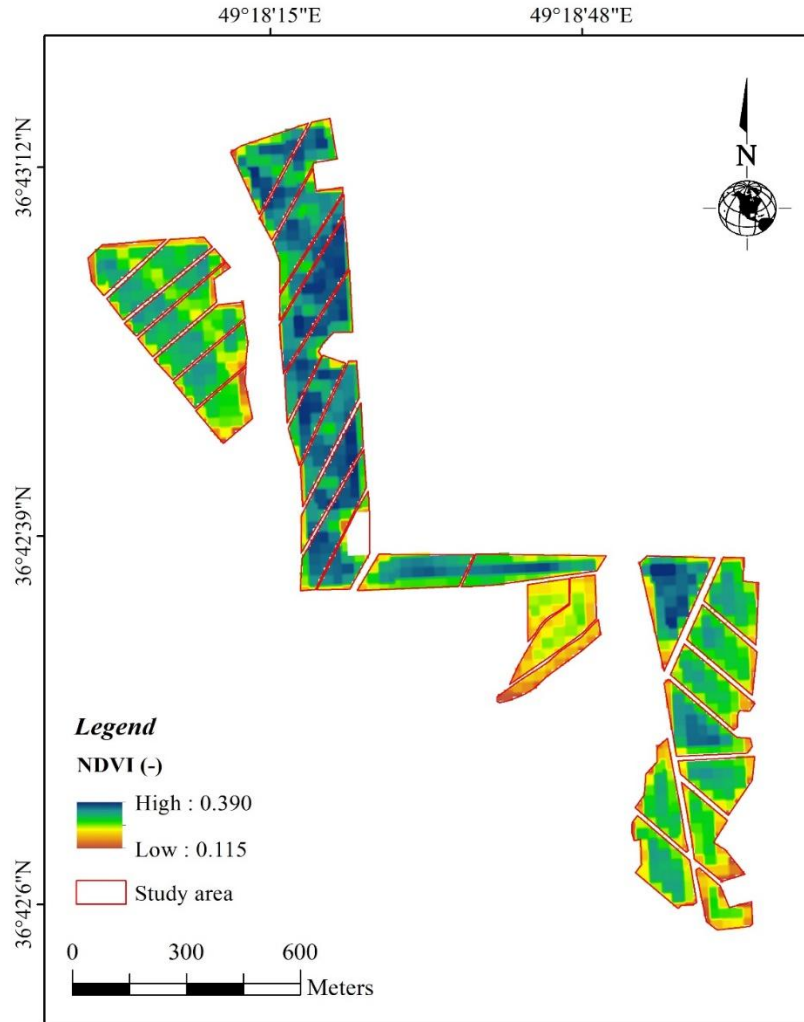


Fig. 7. Spatial distribution of the NDVI derived from satellite imagery of the rectangular SHD olive orchard investigated in this study.

Fig. 8 illustrates the monthly NDVI progression for the 2025 calendar year. Across the observation period from January to December, NDVI values ranged from a minimum of 0.115 to a maximum of 0.39, with an annual mean of 0.27 ± 0.09 . The time-series data show the gradual increase in NDVI from early winter toward spring, followed by a continuous rise that culminated in the uppermost values recorded during midsummer. The plotted curve in Fig. 8 summarizes these monthly fluctuations and provides the numerical sequence of NDVI transitions throughout the year. The seasonal pattern shows a peak NDVI of approximately 0.35 during the summer months, followed by a steady decline extending from July to September. The lowest values, reaching

about 0.14, occurred during the winter interval from December to March. A renewed increase in NDVI began from April through June, marking the transition toward the summer maximum. Fig. 8 therefore presents the full annual NDVI cycle for the studied SHD olive orchards and quantifies the intra-annual variability captured through the Sentinel-based time-series data.

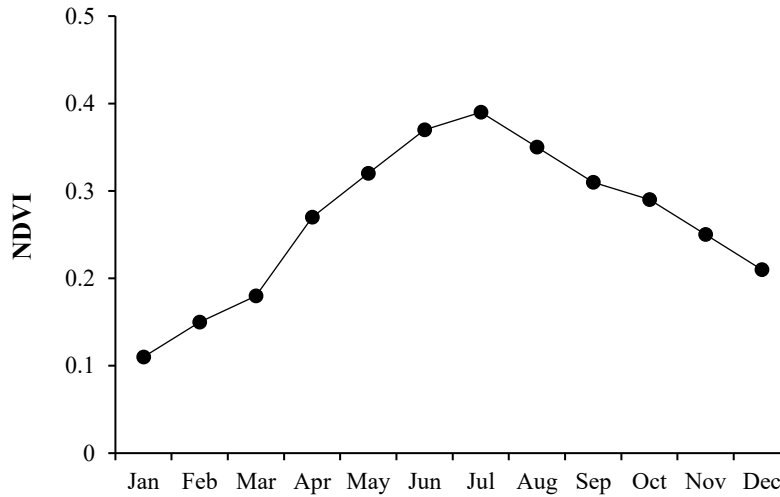


Fig. 8. NDVI time-series over the 2025 growing season for super-high-density (SHD) olive orchards in the Tarom region, Iran.

3.5. Pearson Correlation

Pearson correlations (Table 9) showed that yield exhibited both positive and negative associations with the evaluated nutrients. The strongest positive coefficients with yield were recorded for P% ($r = 0.51$) and Zn% ($r = 0.13$), whereas the smallest coefficient in magnitude corresponded to Ca% ($r = 0.07$). Negative correlations of moderate strength were observed for Mg% ($r = -0.42$) and Mn% ($r = -0.26$), while the remaining nutrient–yield relationships were weak. Among inter-element correlations, the highest value occurred between Fe% and Mn% ($r = 0.67$), followed by N% with K% ($r = 0.54$) and N% with Mg% ($r = 0.53$). Additional positive associations were documented for Cu% with Mn% ($r = 0.40$), K% with Cu% ($r = 0.32$), and P% with Zn% ($r = 0.24$), whereas several pairs showed near-zero or negligible relationships, including Ca% with Mg% ($r = 0.00$) and Zn% with Mn% ($r = -0.00$).

Table 9. Pearson correlation coefficient matrix among leaf nutrient concentrations in olive trees.

Variables	Yield	N%	P%	K%	Ca%	Mg%	Fe%	Mn%	Zn%	Cu%	B%
-----------	-------	----	----	----	-----	-----	-----	-----	-----	-----	----

Yield	1											
N%	-0.22	1										
P%	0.51	0.09	1									
K%	-0.24	0.54	0.33	1								
Ca%	0.07	-0.53	-0.33	-0.15	1							
Mg%	-0.42	0.53	-0.52	0.15	0.00	1						
Fe%	-0.06	0.17	0.02	0.06	-0.18	-0.07	1					
Mn%	-0.26	0.20	-0.05	0.17	-0.14	0.20	0.67	1				
Zn%	0.13	0.08	0.24	0.26	-0.04	-0.19	0.15	-0.00	1			
Cu%	0.17	0.17	0.14	0.32	-0.14	0.07	0.34	0.40	0.04	1		
B%	-0.21	-0.07	-0.13	0.04	0.16	0.19	-0.05	-0.04	0.00	-0.14	1	

As depicted in Fig. 9, the relationships between olive yield, various nutrient diagnostic methods (DRIS, DOP, CND), and NDVI were evaluated. An exceptionally robust positive association was identified between NDVI and crop yield ($r = 0.97$, $p < 0.0001$), aligning with findings reported by Caruso et al.³¹. Conversely, NBI indices showed negligible and statistically insignificant correlations with NDVI ($p \geq 0.05$), with coefficients of -0.02 , -0.24 , and -0.14 for DOP, DRIS, and CND, respectively. P indices, however, displayed meaningful positive correlations with NDVI across all diagnostic approaches; specifically, $r = +0.38$ ($0.01 \leq p < 0.05$) for DOP, and $r = +0.50$ ($p < 0.01$) for both DRIS and CND. Regarding negative trends, the most pronounced inverse correlations were detected between NDVI and both K and B indices within the DOP ($r = -0.44$ and -0.42 , $p < 0.05$) and DRIS ($r = -0.32$ and -0.35 , $p \geq 0.05$) methods, as well as Mn and B in the CND method ($r = -0.28$ and -0.23 , $p \geq 0.05$). Finally, while olive productivity demonstrated significant positive linkages with P-indices ($r = +0.45$, $+0.45$, and $+0.55$; $p < 0.01$), it maintained negative, non-significant associations with the NBI indices. A comprehensive overview of the remaining correlation coefficients is provided in Fig. 9.

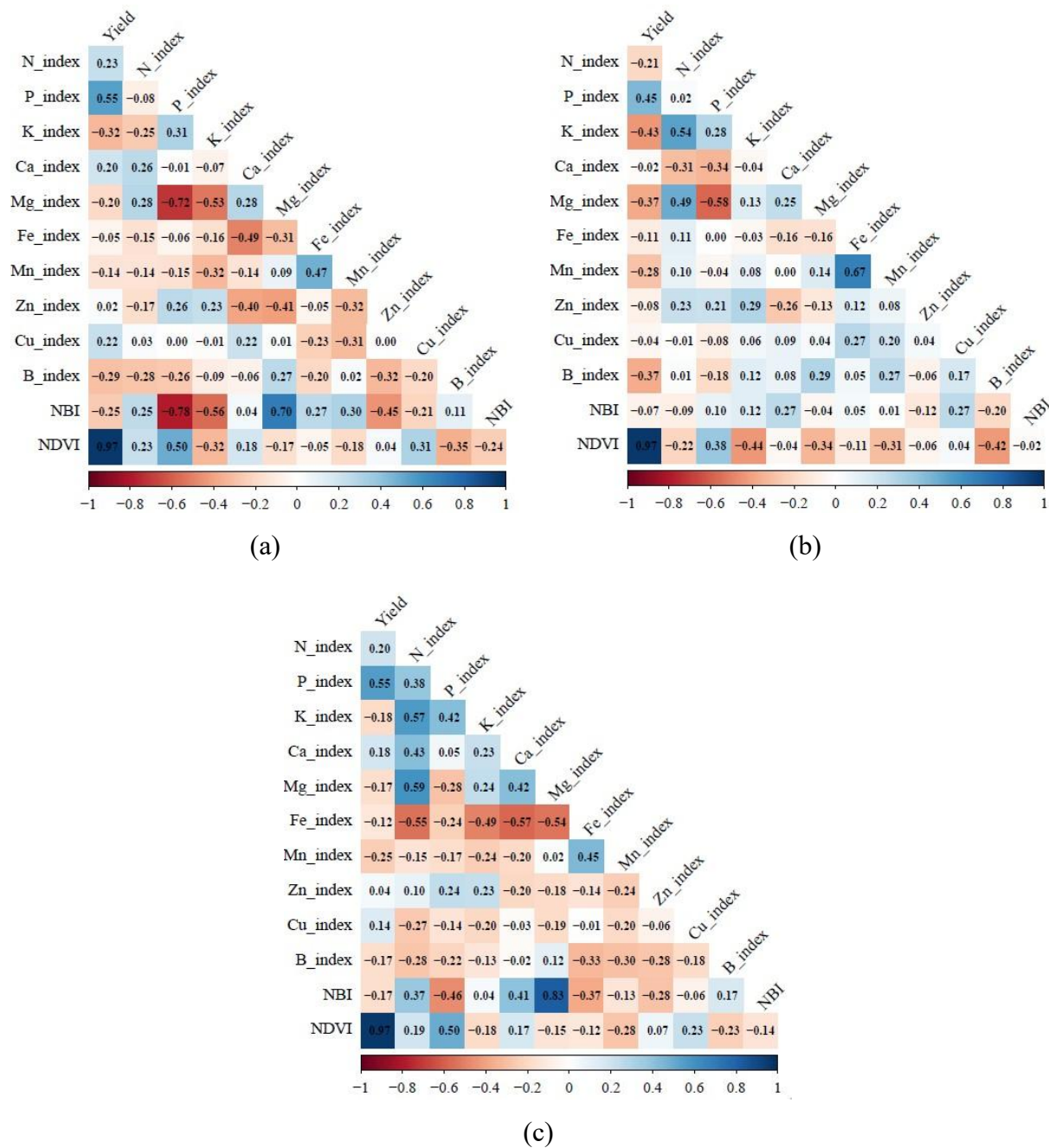


Fig. 9. Correlation analysis between NDVI and the DRIS (a), DOP (b), and CND (c) indices.

4. Discussion

The findings of this study demonstrate that olive productivity in the Tarom region is strongly shaped by the interaction between soil properties, irrigation water quality, and nutrient balance of

SHD orchards. Soil analyses (Table 1 and Fig. 2) revealed a predominantly sandy texture, low organic matter, and moderately alkaline pH, all of which limit nutrient retention and accelerate leaching. These characteristics indicate that the soils function as low-buffering, nutrient-flow systems in which annual productivity relies heavily on externally supplied nutrients rather than on inherent soil fertility. Additionally, the irrigation water (Fig. 3 and Table 2) displayed high electrical conductivity and substantial salt loads, imposing ionic competition and osmotic stress on trees. Such saline conditions intensify nutrient uptake constraints, particularly for K^+ , Ca^{2+} , and several micronutrients, and reduce photosynthetic efficiency by altering metabolic pathways. In high-density and SHD systems, where nutrient removal is substantial due to continuous fruiting and vegetative turnover, these environmental constraints underscore the need for precise, well-timed nutrient management to maintain physiological performance and stable yields^{32, 33}.

The nutrient diagnostic approaches applied in this study (DRIS, DOP, and CND) collectively revealed distinct imbalances between high-yielding and low-yielding orchards. Although mean nutrient concentrations of the high-yielding group generally aligned with established norms (Table 5, 6, and 7), the indices calculated for low-yielding orchards exhibited pronounced deviations (Table 8). All diagnostic methods consistently indicated that N was maintained within or near optimal ranges, suggesting that fertilization programs in the region provide sufficient N inputs. However, the persistently negative indices for P highlight its role as the dominant limiting macronutrient. The strong P deficiency detected by DRIS, DOP, and CND can be attributed to the calcareous, high-pH soil environment (Table 1), where P becomes immobilized via formation of low-solubility Ca-P minerals. Given that P regulates inflorescence initiation, fruit development, and oil biosynthesis, its inadequate availability likely plays a central role in restricting yield potential in many orchards^{34, 35}. In contrast, Mg tended toward excess, reflecting both its high availability in calcareous soils and competitive suppression of K uptake³⁶.

Potassium also showed moderate imbalance, reflecting competitive interactions with abundant Ca^{2+} and Mg^{2+} in these soils. While K deficiency was less severe than that of P, its tendency toward suboptimal levels is consistent with widely documented K–Ca antagonism in calcareous soils³⁷.

Micronutrient imbalances were more severe and widespread. Among them, Zn emerged as the most critically limiting element across orchards, as indicated by consistently negative DRIS, DOP,

and CND values (Table 8). Zinc's role in enzyme activation, hormone regulation, and meristematic growth makes its deficiency particularly detrimental under SHD conditions where continuous canopy renewal is essential. Boron was also frequently deficient, which may directly impair pollen viability, fertilization, and fruit set³⁸. Copper deficiency, though less severe than Zn and B, was also evident in several orchards, likely limiting lignification and disease resistance³⁹. These nutrient patterns collectively align with the nutrient balance indices (NBI, Σ DOP, and CND-r²) presented in Fig. 6, where higher imbalance indices in low-yielding orchards indicate stronger deviations from optimal nutrient ratios. The negative correlation between yield and these imbalance indices demonstrates that nutrient disproportion, not merely absolute concentration, is a primary determinant of yield variability in Tarom's SHD olive orchards.

Comparing diagnostic approaches suggests that each method contributes unique insight, but the CND framework offers particular advantages in capturing multivariate interactions. While DRIS and DOP effectively highlight individual nutrient deviations, CND incorporates compositional data structure and the residual component (Rd), enabling more robust modeling of nutrient interactions and yield responses. The inflection points derived from CND functions (Table 6) provide biologically meaningful thresholds for interpreting nutrient sufficiency in SHD systems. The consistency of nutrient ranking across diagnostic methods (Table 8) further validates the reliability of these techniques for Mediterranean-type calcareous soils. These results align with earlier studies in perennial crops reporting that DRIS and CND are powerful tools for diagnosing nutrient balance under complex soil chemical conditions, particularly where high CaCO₃ and salinity distort nutrient availability⁴⁰.

Integration of NDVI with leaf-based diagnostic techniques provided an additional layer of insight into orchard variability. The NDVI map (Fig. 7) clearly depicted spatial differences in canopy vigor that corresponded to nutritional patterns detected by DRIS, DOP, and CND. Orchards with higher NDVI values typically belonged to the high-yielding group and exhibited more balanced nutrient profiles, whereas orchards with depressed NDVI values aligned with nutrient-limited, low-yielding blocks. Seasonal NDVI patterns (Fig. 8) showed a logical progression with maximum values occurring during the active summer growth period and minimum values in winter. This seasonal trajectory aligns with known physiological patterns of olive trees and reinforces NDVI's

value as a canopy-level indicator of growth performance, vegetative renewal, and potential nutritional stress. These findings support previous research indicating that NDVI is a reliable, non-destructive proxy for canopy density, shoot growth, and water–nutrient status in hedgerow olive orchards^{4, 41}.

According to the correlation patterns presented in Fig. 9, the DOP, DRIS, and CND diagnostic frameworks exhibited broadly comparable behavior. In each of these three approaches, NDVI showed a positive association with the P index, whereas its relationships with the K and B indices were consistently negative. Despite this general agreement, the CND procedure can be regarded as conceptually more robust than DOP and DRIS because it explicitly integrates multivariate interactions among nutrients rather than treating each element in isolation⁴².

The CND- r^2 statistic displayed a very strong positive correlation with Mg (0.83) and moderate positive correlations with Ca (0.41) and N (0.37), supporting the interpretation that these nutrients are relatively adequate in the orchards under study. Conversely, CND- r^2 was negatively correlated with the indices for P (−0.46), Fe (−0.37), and Zn (−0.28). These inverse relationships imply that these elements act as yield-limiting factors and contribute to the overall nutritional disequilibrium of the trees. This interpretation is consistent with the findings of Abbasi-Karvaneh et al.⁴³, who, based on nutrient balance indices derived from DOP, DRIS, and CND, identified Fe and P as the predominant limiting nutrients in low-yield peach and nectarine orchards.

Cultivar-specific responses offer important implications for orchard management. The results showed that ‘Arbequina’ orchards were disproportionately represented in the high-yielding and nutritionally balanced categories, whereas ‘Koroneiki’ orchards were more frequently associated with low yields and higher nutrient imbalance indices. This difference suggests inherent variation in nutrient uptake efficiency, salinity tolerance, and canopy architecture between these cultivars under SHD planting. Considering the region’s sandy soils and saline irrigation water, Arbequina’s relatively higher adaptability may reflect superior root system plasticity or nutrient transport efficiency. This cultivar-level divergence underscores the importance of tailoring fertilization, irrigation, and canopy management to genotype-specific demands.

This study provides a multidimensional assessment of olive nutrition by integrating three complementary diagnostic frameworks (DRIS, DOP, and CND), thereby enabling the

triangulation of nutrient limitations and distinguishing between method-consistent and method-specific findings. Furthermore, by coupling ground-based leaf diagnostics with Sentinel-2 NDVI, this research offers a pathway for up-scaling precision management from individual leaf analysis to remote canopy monitoring. These methodological advancements are particularly critical for super-high-density (SHD) olive systems—a rapidly expanding global model—which face intensified resource competition. By addressing these complexities within the unique agro-ecological context of semi-arid, calcareous, and saline-irrigated environments in Tarom, Iran, this work fills a vital gap in transitioning from general nutritional models to precise, region-specific management strategies.

5. Conclusion

Results from this study demonstrate that precisely characterizing nutrient status in SHD olive orchards on calcareous soils is imperative, given the pronounced nutrient interactions and limited element mobility inherent to such environments. By integrating DRIS, DOP, CND, and NDVI frameworks, a holistic evaluation of the nutritional constraints impacting the Tarom region was achieved, identifying P and K as primary macronutrient limitations in low-yielding orchards, alongside widespread Zn, B, and Cu deficiencies primarily driven by elevated pH and CaCO_3 levels. The strong inverse association between nutrient imbalance indices and fruit yield confirms that nutritional disproportion significantly restricts productivity, while temporal analysis identifies summer as the optimal period for NDVI-based canopy monitoring. Combining remote sensing indices with traditional leaf diagnostics offers a robust approach for refining fertilization, pruning, and stress management protocols. Although NDVI exhibits high correlation with olive yield and P availability, its limited relationship with general nutrient balance indices (NBI) highlights the critical role of P shortages as a specific yield-suppression factor. Consequently, strategic efforts to improve P bioavailability, optimize micronutrient management, specifically for Zn and B, and maintain K homeostasis are essential to enhance yield stability of SHD olive systems under calcareous conditions.

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CRediT authorship contribution statement

Mahrokh Sharifmand: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. Mehdi Taheri: Review & editing, Methodology, Data curation, Conceptualization, Supervisor. Ebrahim Sepehr: Review & editing, Methodology, Data curation, Conceptualization, Supervisor.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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