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Nutrient balances of grain wheat grown in calcareous soils of Iran

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ABSTRACT

Improving the productivity of wheat, Iran's most important staple crop, remains a major agricultural challenge, highlighting the need for more effective nutrient management strategies. Plant-based foods can be enriched with essential micronutrients by increasing their concentration in edible tissues, enhancing their bioavailability, or both. Micronutrient concentration in the edible portions of forage and food crops is governed by multiple complex, dynamic, and interacting factors, including plant genotype, soil properties, environmental conditions, and nutrient interactions. Compositional Nutrient Diagnosis (CND) was applied to evaluate the nutritional balance of macro- (N, P, K) and micronutrients (Fe, Mn, Zn, and Cu) in wheat grain (*Triticum aestivum* L.) cultivated under different fertilization systems in Iran. For the low-yielding subpopulation, the dominant CND indices controlling yield variability in the dataset were I_{Fe}, I_P, and I_K, whereas for the high-yielding subpopulation, I_{Mn}, I_K, and I_P were most influential. These findings indicated that Mn deficiency was determined as the most yield-limiting factor, followed by K and P. In contrast, Zn and Fe were not identified as critical limitations, as their bioavailability was enhanced by micronutrient fertilizer application. Zinc treatments recorded the highest frequency in the excellent and good clusters (96.9%), followed by compost (93.8%) and Fe treatments (87.5%). This study identifies previously unreported limiting factors in grain wheat following the application of nutrients from inorganic, organic, and integrated nutrient sources. Practically, by identifying the most limiting nutrients, the CND approach may enable more precise fertilizer recommendations, thereby improving nutrient use efficiency, grain quality, and wheat yield in future crop management.

Keywords: Compositional Nutrient Diagnosis (CND), nutrient index, balance index, fertilizer recommendation, micronutrients, irrigated wheat.

1. Introduction

Soil fertility is an important plant growth-limiting factor (Magallanes-Quintanar et al., 2006). Achieving higher crop yields depends not only on balanced fertilization but also on accurate, site-specific nutrient management strategies. Conventional approaches to soil fertility diagnosis, however, are insufficient to meet this demand in solution (Urricariet et al., 2004). Soil, water, and plant test data can be used to optimize fertilizer use, increase both the quantity and quality of crop yields, and minimize the environmental risks associated with excess nutrient application (Daryashenas et al., 2020). Although soil analysis is widely used to estimate nutrient availability, nutrient concentrations in soil are not always related to yield in most fruit and grain crops, particularly for micronutrients in calcareous soils where pH-driven immobilization decouples soil test values from actual plant nutrient status (Rozane et al., 2020; Shehu et al., 2023; Wei et al., 2006). Sole reliance on soil testing therefore increases the probability of errors in results interpretation and fertilizer recommendations. Integrating plant-based diagnostic approaches with soil analyses offers a more robust framework to predict crop nutrient requirements under field conditions (Babazadeh Jafari et al., 2024; Ziadi et al., 2007). Plant-based nutrient diagnostic tools are based on two methodological frameworks: (*i*) nutrient concentration-based approaches including critical minimum values or critical nutrient range (CNR) (Bates, 1971), and (*ii*) ratio-based approaches, most notably the Diagnosis and Recommendation Integrated System (DRIS) (Daryashenas et al., 2018; Walworth and Sumner, 1987). Despite their widespread use, both methods have documented limitations. The CNR method does not account for nutrient interactions, the traditional range of normality, or classification of nutrient status into categories such as deficiency, sufficiency, luxury consumption, and excess (Parent et al., 2009).

While the more sophisticated methods, such as the DRIS approach, take into account some of these shortcomings by incorporating pairwise nutrient relationships (Ferrández-Cámara et al., 2021) and providing easily interpretable nutrient indices derived from a large number of nutrient ratios (Walworth and Sumner, 1987), it too has inherent problems. These include redundancy in dual and two-component amalgamated ratios, an artificially enlarged dataset, and one redundant index that closes the system to zero and is computable from the remaining indices (Parent et al., 2012). Furthermore, both CNR and DRIS disregard the compositional nature of analytical data and are prone to bias when dealing with a high number of ratios. The use of orthogonal balances, which constrains the number of ratios that can be independently diagnosed within a given composition, avoids these biases and represents a conceptually sounder diagnostic framework (Daryashenas et al., 2018). Building on these principles, the CND (Compositional Nutrient Diagnosis) method (Parent and Dafir, 1992) was developed as a more theoretically rigorous alternative. CND integrates nutrient concentration in plant leaves, all possible nutrient interactions, and crop yield data to estimate critical levels or sufficiency bands for individual elements, and to detect nutrient deficiency and/or excess (Parent and Dafir, 1992; Rozane et al., 2020). Unlike DRIS, CND nutrient indices indicate whether a nutrient insufficiency can be corrected by supplying a single nutrient or by exploiting multiple nutrient interactions to improve overall nutrient balance (Parent and Dafir, 1992). CND is also applicable to small-sized crop nutrient datasets, which is a practical advantage in field-based studies (Khiari et al., 2001). Its relative ease of use in diagnosing nutritional imbalances has led researchers to desire CND over the other approaches (Wairegi and van Asten, 2011). Accordingly, CND has been applied to diagnose crop nutrient status for numerous crops under different fertilizer management systems in Iran (Abbasi-Karvaneh et al., 2024; Babazadeh Jafari et al., 2024; Basirat et al., 2016; Daryashenas et al., 2020; Daryashenas et al., 2026; Daryashenas et al., 2018; Deligani et al., 2023; Geiklooi et al., 2021; Ghaderi et al., 2025; Ghaderi et al., 2023; Ghoreyshi et al., 2024; Mahmoodi Nezhad Dezfully and Mostashari, 2022; Majidi et al., 2022; Mostashari et al., 2020; Mostashari et al., 2022; Sharifmand et al., 2018; Tadayon et al., 2022; Zandi et al., 2021; Zolfi Bavariani et al., 2022).

Wheat (*Triticum aestivum* L.) is among the most economically important and nutrient-demanding grain crops worldwide, with approximately 6.5 million hectares under cultivation in Iran. (Geiklooi et al., 2021). Despite this agronomic significance, published information on CND-derived nutrient norms for grain wheat in Iran remains limited. Geiklooi et al. (2021) Critical CND indices and corresponding nutrient norms for wheat leaves grown under specific agro-industrial conditions at Moghan Company situated in Ardabil Province, Northwest of Iran; however, this work was confined to a narrow set of cultivars and management conditions, leaving a substantial knowledge gap with respect to nutrient balance norms across contrasting fertilizer management systems. However, no CND norms have been derived for grain wheat across different fertilizer systems- inorganic, organic, and integrated- although fertilizer management changes the stoichiometric relationships among leaf nutrients as reported previously by (Abbasi-Karvaneh et al., 2024; Zandi et al., 2021). The present study therefore aimed to derive CND-based nutrient norms for grain wheat under inorganic, organic, and integrated fertilizer management systems, providing a broader diagnostic reference applicable to diverse production conditions.

2. Materials and Methods

2.1. Data collection

Data were collected from Google Scholar and the Scientific Information Database (SID, https://sid.ir) for peer-reviewed papers reporting the effects of fertilizer application on grain yield and nutrient concentration in wheat, restricted to experiments conducted in Iran. Search terms included: wheat, fertilizer, nutritional elements, macronutrients, micronutrients, zinc, iron, manganese, copper (including elemental symbols), and yield. Studies were included if they met all of the following criteria: 1) the experiment was conducted under field conditions in Iran, with clearly reported fertilizer types and application rates, 2) grain concentrations of at least two nutrient elements were measured and reported, 3) when grain nutrient uptake rather than concentration was reported, grain concentration was back-calculated by dividing uptake by grain yield, 4) where data were presented exclusively in graphical form, numerical values were extracting using WebPlotDigitizer-4 (http://getdata-graph-digitizer.com/download.php), 5) only irrigated wheat experiments were included; studies conducted under abiotic stress conditions (e.g., heavy metal contamination, salinity, water deficiency (or drought)) were excluded. During screening, an additional verification method was used for each candidate study that (*i*) the experimental design and number of replications were clearly reported, and (*ii*) the analytical method used for nutrient determination was specified; studies failing to report these details were also excluded. The final dataset comprised 602 treatment comparisons drawn from 33 publications.

2.2. Compositional nutrient diagnosis

CND norms and indices were computed following the procedures of Parent and Dafir (1992). Nutrient arrangement was expressed as a d-dimensional simplex (S^d), with a filling value (R_d) accounting for the remaining plant-tissue composition, computed as:

S^d=[(N,P,K,...,R_d):

$$N>0,P>0,K>0,...,0,N+P+K+...+R_d+100 \quad [1]$$

$$R_d=100-(N+P+K+...) \quad [2]$$

where N, P,..., K, were represent nutrient proportions (%), 100 represents total dry-matter concentration (%); and R_d is the filling value between 100% and the sum of d measured nutrient proportions.

The geometric mean (G) of the d+1 components, including the d nutrient proportions and Rd nutrient proportions, was computed as follows. Aitchison (1982):

$$G = \left[N.P.K...R_d \right]^{\frac{1}{d+1}} \quad [3]$$

Row-centered log ratios (V_x) were then derived as:

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

$$... \quad V_{R_d} = \ln\left(\frac{R_d}{G}\right) \quad [4]$$

and

$$V_N + V_P + V_K + ... + V_{R_d} = 0 \quad [5]$$

where V_X is the CND row-centered log-ratio expression for nutrient X, and Eq. (5) serves as a control to ensure that the log-ratio computations sum to zero across all components.

CND indices were calculated as:

$$I_N = \frac{(V_N - V_N^*)}{SD_N^*}, \quad I_P = \frac{(V_P - V_P^*)}{SD_P^*}, \quad I_K = \frac{(V_K - V_K^*)}{SD_K^*}$$

$$... \quad I_{R_d} = \frac{(V_{R_d} - V_{R_d}^*)}{SD_{R_d}^*} \quad (6)$$

where $I_N, I_P, I_K, \ldots, I_R$ are the CND indices for d nutrients, $V^*_N, V^*_P, V^*_K, \ldots, V^*_R$, and $SD^*_N, SD^*_P, SD^*_K, \ldots, SD^*_{Rd}$ are the means and standard deviations of the row-centered log ratios, respectively, derived from the high-yield subpopulation.

To partition observations into high- and low-yield subpopulations, the Cate–Nelson ANOVA procedure (Cate and Nelson, 1971) was applied as described by Magallanes-Quintanar et al. (2006). This approach was preferred over conventional yield-target methods because the latter do not provide a statistically defined minimum yield cutoff for subpopulation separation. (Khiari et al., 2001). Because some studies reported biological yield while others reported grain yield -both accompanied by grain nutrient concentrations- subpopulation partitioning was performed separately for biological yield (n = 228) and grain yield (n = 574), with the two datasets treated independently in subsequent analyses.

2.3. Diagnosis of nutrient balances in grain wheat with CND

The CND indices as defined by Eq. 6 were standardized and linearized variables as dimensions of a circle (d+1 =2), a sphere (d+1=3), or a hypersphere (d +1 > 3) in a d+1 dimensional space (Magallanes-Quintanar et al., 2006). The overall nutrient balance status of each treatment was calculated using the CND balance index (r^2), defined as:

$$r^2 = I_N^2 + I_P^2 + I_K^2 + ... + I_{R_d}^2 \quad [7]$$

where r^2 represents the mean of nutrient imbalances index of CND. Higher r^2 values indicate greater overall nutrient imbalance, as they reflect larger aggregate deviations from the norms established for the high-yield subpopulation. (Huang et al., 2012; Magallanes-Quintanar et al., 2006).

2.4. Cluster analysis

Cluster analysis was employed to classify the treatment observations into grain yield homogeneous groups, enabling identification of distinct fertilization response patterns within the dataset. A two-stage clustering procedure was adopted. First, hierarchical cluster analysis using Ward's minimum variance method, with squared Euclidean distance as the dissimilarity measure, was applied to determine the optimal number of clusters from the agglomeration schedule and dendrogram. (Ramazani and Abdipour, 2019). Second, *k*-means cluster analysis was performed using the number of clusters identified in the hierarchical step to refine group membership and maximize within-cluster homogeneity; convergence was achieved after 16 iterations. Differences in yield among clusters were evaluated using one-way analysis of variance (ANOVA). All statistical analyses were performed using the Statistical Package for the Social Sciences (SPSS, 26, IBM Corp., Armonk, NY, USA).

3. Results

3.1. Grain yield of wheat

Grain yield of wheat across the compiled dataset ranged from 1000 to 10,333 kg ha^{-1}, with an overall mean of 5094±2002 kg ha^{-1}. The lowest recorded grain yield of wheat was reported for the wheat variety Back Cross Rushan grown following Sorghum residues (Khoshgoftarmanesh et al., 2017). In contrast the highest was recorded for durum wheat receiving foliar application of $FeSO_4$ at 8 g L^{-1} application. These extremes highlight the substantial variability introduced by both genetic and management factors. Grain yield is a complex trait governed by the interaction of soil properties, fertilization system, and cultivar characteristics and predominant environmental conditions (Hasheminasab et al., 2023).

Cross-tabulation of treatments against yield clusters revealed distinct associations between management conditions and productivity classes. Treatments/conditions associated with optimal nutrient supply and favorable soil and climatic conditions were disproportionately represented in the high-yielding clusters, whereas those conducted under limiting edaphic or climatic conditions were predominated in low-yielding subpopulations. Given the diversity of field trial locations and cultivars included in this dataset, these differences likely reflect the combined influence of genetic potential, soil characteristics, and site-specific climatic variability rather than any single management factor.

The inflection point separating the low- from high-yielding subgroups was identified at a mean grain yield s

Table 1. Wheat grain yield classification based on Ward's method

Cluster	Mean grain yield (kg ha⁻¹)	Interpretation	Number of observations	Percentage
1	8008.67	High yield	73	12.7
2	6426.82	Moderately high yield	184	32
3	5042.86	Moderate yield	146	25.4
4	2476.08	Poor yield	172	29.9

Table 2. Wheat CND norms (row-centered ratios and standard deviations, SD) for d=2-7 nutrients in a high-yield subpopulation and their associated mean nutrient concentrations and standard deviations

Row-centered log ratio	CND nutrient norms		Nutrient	nutrient concentrations		
	Mean	SD			Mean	SD
V^*_N	1.55	0.99	N	%	1.94	0.32
V^*_P	0.60	1.34	P	%	0.33	0.11
V^*_K	1.31	0.86	K	%	0.39	0.09
V^*_{Fe}	-2.95	1.02	Fe	mg kg^{-1}	77.92	36.64
V^*_{Mn}	-3.28	1.06	Mn	mg kg^{-1}	43.78	16.91
V^*_{Zn}	-4.49	1.19	Zn	mg kg^{-1}	32.96	10.39
V^*_{Cu}	-4.40	0.67	Cu	mg kg^{-1}	5.82	3.14
V^*_{Rd}	5.73	1.18	Rd	%	98.26	0.80
$\sum V^*_x$	0	-				

of 4676± 59.47 kg ha^{-1}, which aligns closely with reference thresholds of 4232 kg ha^{-1} for rainfed wheat (Geiklooi et al., 2021) and 5500 kg ha^{-1} for irrigated wheat (Hasheminasab et al., 2023), lending external validity to the classification boundary.

Hierarchical cluster analysis using Ward's method indicated an optimal four-cluster solution, subsequently confirmed by *k*-means clustering. The algorithm converged after 16 iterations, indicating stable cluster membership. Mean grain yield differed substantially among clusters, ranging from 2476.1 to 8008.7 kg ha^{-1} (Table 1). Cluster 1 represented the highest-yielding group (8008.67 kg ha^{-1}), followed by Cluster 2 (6426.8 kg ha^{-1}), Cluster 3 (5042.9 kg ha^{-1}), and Cluster 4 (2476.1 kg ha^{-1}), with 73, 184, 146, and 172 observations assigned to each group, respectively. One-way ANOVA confirmed strong descriptive differences among clusters for grain yield ($F = 2317.65$, $P < 0.001$).

The relatively low proportion of observations in the high-yielding Cluster 1 (12.7%) suggests that grain yields exceeding 8000 kg ha^{-1} were difficult to attain and may depend on optimal environmental conditions and effective agronomic management. In contrast, the largest share of observations fell within the moderate-yielding Cluster 2 (32.0%). In comparison, 29.9% of observations were grouped into the low-yielding subpopulation, indicating that suboptimal conditions limiting yield were prevalent across a substantial proportion of the compiled studies.

3.2. Compositional nutrient diagnosis norms for simplex S^d

To characterize the nutritional basis of these yield differences, CND analysis was applied.

Because individual studies reported between two and seven macro- and micronutrients, the compositional simplex S comprised three to eight components (i.e., (d+1)-dimensions), incorporating reported elements (N, P, K, Fe, Mn, Zn, and Cu) together with a filling value R estimated using Eq. (1). Nutrient concentrations were transformed into CND row-centered log ratios V_N, V_P, V_K, V_{Fe}, V_{Mn}, V_{Zn}, V_{Cu}, and V_R using Eqs. (2) to (4). CND norms derived from the high-yield subpopulation, including row-centered ratios, standard deviations, and mean nutrient concentrations, are reported in Table 2 for d=2 to 7 nutrients.

3.3. Diagnosis of nutrient balances in grain wheat with CND

The nutrient balance index (r^2) ranged from 0.0 to 30.0 in the high-yield subpopulation, with a mean of 3.96, compared with a range of 0.21 to 20.13 with a mean of 5.12 in the low-yield subpopulation (Tables 3 and 4). The higher mean r^2 in the low-yield group, and its greater spread, indicate more pronounced and heterogeneous nutritional imbalances among underperforming observations. In CND theory, values of r^2 approaching zero reflect a nutrient balance closest to the defined norm

Table 3. Descriptive statistics of CND nutrient indices (I_X), the CND nutrient balance index (r^2), and deficiency order related to high-yield population

	I_N	I_P	I_K	I_{Fe}	I_{Mn}	I_{Zn}	I_{Cu}	I_{Rd}	r^2	Deficiency order
Min	-2.35	-2.41	-3.60	-2.00	-2.00	-1.00	-4.00	-2.00	0.00	Cu<K<P<N<Fe<Mn<Zn
Max	2.55	1.43	1.20	3.00	1.00	2.00	2.00	3.00	30.00	Mn<K<P<Zn<Cu<N<Fe
Mean	0.00	0.00	0.00	0.02	0.00	0.03	0.00	0.00	3.96	
SD	1.00	1.01	1.02	1.02	1.00	0.99	1.01	1.00	5.03	
N	348	70	27	191	133	343	59	387	402	

Table 4. Descriptive statistics of CND nutrient indices (I_X), the CND nutrient balance index (r^2), and deficiency order related to low-yield population

	I_N	I_P	I_K	I_{Fe}	I_{Mn}	I_{Zn}	I_{Cu}	I_{Rd}	r^2	Deficiency order
Min	-2.40	-2.96	-3.81	-3.83	-1.83	-1.45	-0.91	-2.03	0.21	Fe<K<P<N<Mn<Zn<Cu
Max	2.45	1.09	1.24	1.71	1.11	2.23	2.70	2.00	20.13	P<Mn<K<Fe<Zn<N<Cu
Mean	0.46	-0.27	-0.11	-0.41	0.24	0.27	0.29	0.37	5.12	Fe<P<K<Mn<Zn<Cu<N
SD	1.07	1.13	1.07	1.11	0.46	0.90	1.10	0.86	5.14	
N	173	142	63	127	67	183	57	182	212	

and are associated with the highest probability of achieving high yield (Geiklooi et al., 2021).

4. Discussion

4.1 Nutrient interactions through CND

Mean concentrations of N, P, K, Fe, Mn, Cu, and Zn in wheat grain are presented in Table 5. Concentrations across the high-yielding subpopulation were broadly consistent with CND-derived norms and reference ranges reported in the literature (Hasheminasab et al., 2023; Mesfin et al., 2026). Mean Fe concentration (78 mg kg^{-1}) exceeded the value reported by Hasheminasab et al. (2023) and surpassed the human health adequacy threshold of 57 mg kg^{-1}, not that Fe was abundant independent of fertilization. This grain-level Fe should not be considered as evidence that soil Fe availability was non-limiting across the dataset. Grain Fe concentration enhanced because of Fe fertilization (notably $FeSO_4$ and Fe-chelate) was applied at higher rates within high-yield clusters. Mean Zn concentration (33 mg kg^{-1}), however, remained below the recommended dietary threshold of 41mg kg^{-1} (Hasheminasab et al., 2023), indicating that Zn biofortification potential was not fully realized even under high-yield conditions. This disagreement between Fe sufficiency and Zn deficiency in grain points to a difference in fertilization efficiency between the two elements.

CND nutrient indices for the high-yielding subpopulation revealed a compositional imbalance characterized by two distinct deficiency sequences. The minimum-concentration deficiency order (Cu<K<P<N<Fe<Mn<Zn) identifies Cu and K as the most limiting nutrients, while Zn and Mn occupy the least limiting. The maximum-concentration deficiency order (Mn<K<P<Zn<Cu<N<Fe) indicates a marked shift in relative nutrient proportions with Fe and N reaching the highest concentrations. This shift may reflect favorable conditions for N and Fe uptake, cultivar-specific remobilization capacity, or differential sink strength during grain filling, though the underlying mechanisms require further investigation. These compositional patterns are partially mirror Geiklooi et al. (2021), who attributed wheat yield depression in wheat to multi-nutrient imbalance involving simultaneous deficiencies of Zn, Cu, Fe, Mn, and B alongside excesses of N, K, Ca, Mg, and P. The match in the present dataset is limited to the excess side: N and Fe excess is consistent with Geiklooi et al. (2021) pattern. The deficiency side diverges: Geiklooi et al. (2021) reported Fe as deficient, whereas in this dataset Fe was in excess and Zn occupied the least-deficient position on the minimum-order ranking rather than being among the most deficient elements as in their study. This divergence is probably explained by the predominance of Fe fertilization within the high-yielding subpopulation analyzed here.

The observed nutrient status patterns reflect complex interactions among applied inputs across the collected studies. Nitrogen nutrition was improved through diverse organic and inorganic sources, including urea, farmyard manure, compost, and sewage sludge.

These N inputs may have indirectly influenced micronutrient dynamics. As noted by Stukenholtz et al. (1966), adequate N supply promotes Zn uptake while

Table 5. Comparing experimental and reference sources of critical values of elements for the analysis of wheat grain based on a high-yielding sub-population

N	P	K	Fe	Mn	Zn	Cu	Reference
	%			mg kg^{-1}			
1.94±0.32	0.33±0.11	0.3±0.03	77.92±36.64	43.78±16.91	32.96±10.39	5.82±3.14	This study
-	-	-	12.35–83.10	9.45–62.65	8.50–70.70	0.06–15	(Hasheminasab et al., 2023)
0.85-2.34	0.2-0.3	0.3-0.4					(Mesfin et al., 2026)

enhancing P utilization efficiency, and elevated K availability can partially reduce the depressive effect of P on Zn acquisition. While this mechanistic framework dates to early nutrient interaction research, its relevance persists in contemporary agronomic contexts, particularly under high-input cropping systems.

Phosphorus management emerged as a critical determinant of micronutrient availability. Cluster-wise analysis revealed that high-rate TSP applications (75 and 125 kg ha^{-1}) were predominantly associated with low-performing yield clusters. In contrast, combined application of organic amendments and Zn fertilizers was linked to measurable increases in plant-available soil P and EDTA-extractable Zn (Manzeke et al., 2014). The negative association between high P inputs and micronutrient availability is mechanistically consistent with evidence that excess P intensifies Zn, Fe, Cu, Mn, and Mo deficiency through precipitation and competitive antagonism in both soil and plant systems (Mesfin et al., 2026; Murphy et al., 2008). These dynamics are particularly relevant in the Iranian context, where chronic imbalance in primary nutrient application, especially P, has led to its accumulation in major farming areas, with documented consequences for soil Zn and Fe availability (FAO, 2005).

The release of native K induced by inorganic P fertilizers has been reported as a secondary interaction pathway (Zhou and Huang, 1995; Zhou and Huang, 2007; Zia et al., 1998), further complicating the nutritional response to P-based management. At the treatment level, Fe-based fertilization particularly $FeSO_4$ and Fe-chelate at higher application rates was more frequently associated with high-yielding clusters. Among micronutrient treatments, Zn application showed the strongest association with superior yield classes, appearing in 96.9% of excellent and good clusters, followed by compost (93.8%) and Fe treatments (87.5%). This pattern emphasizes the primacy of Zn and Fe under the agronomic conditions represented in this dataset. The strong association of Zn and Fe with high-yielding clusters fits known patterns in calcareous soils. Both elements are widely reported as the most limiting micronutrients for wheat in these soils. Zinc deficiency is a particular concern. High soil pH lowers Zn solubility and root uptake. This happens even when total soil Zn reserves are adequate in calcareous soils, the total amount of zinc is generally sufficient, but its concentration in soil solution and consequent bioavailability is very low due to soil conditions such as high pH. Meta-analytic evidence supports this pattern. Soil-applied Zn fertilization led to grain yield increases of up to 27.2% in Zn-deficient soils, compared with more modest gains from foliar application. This may explain why Zn was the micronutrient most consistently linked to superior yield clusters in the current dataset (Hui et al., 2025; Qamari et al., 2023).

Fe-based treatments showed a similar pattern. This includes both $FeSO_4$ and Fe-chelate forms. The explanation likely lies in soil chemistry. High pH and high bicarbonate also constrain Fe solubility. Chelate type matters under these conditions. Conventional EDTA-Fe loses effectiveness above pH 6.8 because Ca^{2+} competes for binding EDTA chelates Fe primarily at pH<6.3 and becomes ineffective at pH>6.8. Other chelates remain effective at the higher pH typical of calcareous soils (Sekhon, 2003).

Compost commonly co-occurred with both Zn and Fe in high-performing clusters. One probable explanation involves organic matter chemistry. Organic functional groups can chelate several metal cations at once, not just organic functional groups such as -COOH and -OH chelate multiple metal ions including Zn^{2+}, Fe^{3+}, and Cu^{2+}simultaneously. This may explain why compost appeared along with both Zn and Fe treatments rather than acting as an independent driver (Batool et al., 2026).

In addition, high pH (>7.5) and elevated $CaCO_3$ content reduce micronutrient solubility through precipitation, adsorption onto carbonate surfaces, and occlusion within calcite crystals, directly linking these mechanisms to the observed Mn and Zn deficiency patterns in the dataset (Beyyavaş et al., 2026).

5. Conclusion

The CND approach successfully characterized the nutrient balance status of wheat grain grown in calcareous soils of Iran across inorganic, organic, and integrated fertilizer systems. Manganese (Mn), potassium (K), and phosphorus (P) were identified as the primary limiting nutrients across all systems. The CND-based multivariate assessment identified Mn as an independent primary nutritional limitation, a distinction that conventional single-element diagnostic approaches are structurally unable to resolve. Among the fertilizer systems evaluated, the integrated system demonstrated the most favorable nutrient balance, indicating that neither inorganic nor organic inputs alone are sufficient for balanced nutrition in calcareous soil environments.

These findings suggest that fertilizer recommendations for irrigated wheat in calcareous soils of Iran should be revised to obviously account for Mn, K, and P, calibrated to soil buffering capacity and crop growth stage. Future research should determine the threshold CND indices at which yield responses to these nutrients become economically significant, and assess whether the Mn-Fe antagonism in high-pH soils persists across growing seasons and under integrated fertilizer systems.

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