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Multivariate Correlation of the Physicochemical and Sensory Profile of Milk Quality from Small Producers in Barranca, Lima-Peru

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Abstract

The comprehensive quality assessment of raw milk from small-scale producers remains essential for improving dairy sector competitiveness. This study employed a multivariate approach to correlate the physicochemical, colorimetric, and sensory profiles of raw milk from eleven producers in the town of Supe, Barranca, Lima, Peru. Milk samples were analyzed using a Lactoscan MCC ultrasonic analyzer, CIEL*a*b* colorimetry, and the Flash Profile sensory method. Data integration and interpretation were performed using Analysis of Variance (ANOVA), Generalized Procrustes Analysis (GPA) and Hierarchical Multiple Factor Analysis (HMFA). The results revealed significant heterogeneity, identifying two distinct producer groups. A high-quality group (DF7, DF10, DF11) presented adequate physicochemical parameters: high fat content (>3.77%), total solids (>12.06%), normal freezing point (≈−0.53 °C), creamy color (high L* and b*), and positive sensory attributes ("fatty", "creamy"). In contrast, a low-quality group (DF4, DF5, DF8, DF9) showed evidence of water adulteration (12–16%), reflected in an elevated freezing point (up to −0.44 °C), low solids-not-fat, and defective sensory profiles ("tasteless", "salty"). The HMFA demonstrated a strong concordance between instrumental and sensory data sets, identifying water adulteration and fat content as the primary drivers of quality variation. This integrated methodology provides a robust diagnostic tool for quality-based payment systems and targeted technical assistance, offering a replicable model for enhancing quality control and valorizing raw milk in smallholder dairy systems.

Keywords: raw milk; quality; dairy farmers; flash profile; colorimetry

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1. Introduction

Milk is an essential food in the human diet, recognized for its high nutrient density, including high-quality proteins, fats, carbohydrates, vitamins, and minerals [1]. Its quality not only directly influences its nutritional value but also determines shelf life, processability, and consumer acceptance [2]. Beyond its nutritional significance, milk serves as a raw material for a vast array of dairy products, making its compositional integrity a cornerstone of the entire dairy value chain. This quality results from a complex interaction between physicochemical parameters (e.g., pH, acidity, fat, protein, and total solids) and sensory attributes (such as color, flavor, and odor), which together define the overall perception of the product [3]. Understanding these interactions is particularly critical in raw milk, where variations directly propagate through processed products, affecting both industrial efficiency and final consumer satisfaction [4].

In developing countries, milk production in smallholder systems plays a fundamental role in food security and the local economy [5]. These systems contribute significantly to rural livelihoods, poverty alleviation, and the nutritional well-being of millions of families. However, they often face significant challenges in maintaining and standardizing product quality, due to variations in cattle feeding, milking practices, post-milking handling, and storage conditions [6]. The lack of technological infrastructure, limited access to quality control systems, and insufficient technical training exacerbate these challenges, leading to marked heterogeneity in the final product. The Supe basin, located in the province of Barranca, Peru, is a traditional livestock area where milk represents a key product. This region, characterized by its coastal valley geography and small-scale farming systems, produces milk that supplies local markets and small-scale dairies. Assessing milk quality in this context is crucial to add value, improve competitiveness, and ensure the safety of the local dairy chain [7]. Furthermore, understanding the specific quality attributes of milk from this region can open opportunities for geographical indication strategies and premium market positioning, thereby enhancing the economic viability of smallholder producers.

Traditionally, milk quality assessment has been approached in a univariate manner, analyzing physicochemical and sensory parameters in isolation. However, such an approach fails to capture the complex interrelationships among these variables [8]. For instance, fat and protein composition not only affect cheese yield but also influence viscosity and consumer-perceived flavor [9]. Likewise, acidity and pH serve as indicators of freshness and are often correlated with the development of undesirable flavors [10]. Moreover, color parameters, often overlooked in routine quality assessments, provide valuable information about feeding regimes (particularly carotenoid content from pasture) and potential thermal treatments [11]. The challenge lies in integrating these diverse data types into a coherent framework that reflects the multidimensional nature of milk quality.

In recent years, multivariate analytical techniques have emerged as powerful tools in food science [12]. Principal Component Analysis (PCA) enables dimensionality reduction and visualization of natural groupings among samples. Generalized Procrustes Analysis (GPA) allows for the comparison of sensory configurations from different assessors, providing a consensus configuration that captures shared perceptions. Hierarchical Multiple Factor Analysis (HMFA) extends this capability by integrating multiple data tables, such as physicochemical measurements and sensory evaluations, into a single analytical framework [13]. These methods enable the identification of hidden patterns within complex datasets, reduce variable dimensionality, and, most importantly, establish relationships between instrumental properties and human sensory perception [14]. This holistic approach to quality assessment can identify the key parameters that most strongly influence product acceptability [15]. The practical implications extend beyond academic characterization:

establishing robust correlations between rapid instrumental measurements and sensory outcomes enables the development of predictive quality models. Such models would allow dairy processors and cooperatives to implement cost-effective screening protocols, ensuring consistent quality and enabling quality-based payment systems that incentivize best practices among producers [16].

The global dairy sector is increasingly moving toward precision livestock farming and quality-based procurement systems. In this context, smallholder producers risk marginalization unless they can demonstrate consistent quality and adopt quality assurance practices [17]. Research that characterizes local production systems and identifies quality determinants provides the scientific basis for targeted interventions, including training programs, infrastructure investments, and policy development. Furthermore, from a food safety perspective, identifying adulteration practices (such as water addition) and hygienic issues (reflected in elevated conductivity and pH changes) enables regulatory authorities and producer associations to implement corrective measures and safeguard public health [18].

Multivariate techniques have been implemented in controlled industrial environments or within well-established dairy systems in developed economies. In this context, standardized production practices reduce the inherent variability that characterizes small-scale producer systems, where quality determinants are often affected by multiple interrelated factors, including feed diversity, milking hygiene, and adulteration practices [6,19]. The international scientific gap lies not in the application of multivariate methods per se, but rather in the integration of these techniques within a unified analytical framework specifically designed to unravel the determinants of quality in small-scale producer dairy systems where adulteration, compositional variability, and sensory defects coexist. Previous studies have employed multivariate approaches for authenticating geographic origin, discriminating between feeding systems, or predicting technological properties [20–22], but few simultaneously address the full spectrum of quality dimensions (physicochemical integrity, colorimetric properties, and sensory perception) within a single analytical framework designed for heterogeneous production contexts. The methodological advance of this study lies in two specific contributions. First, we propose a sequential analytical framework that integrates univariate analysis (identifying adulteration using freezing point), colorimetric characterization (linking feeding regimes), sensory analysis (capturing sensory attributes), and multivariate growth factor analysis (establishing correlations between study data), providing a replicable template for quality assessment in heterogeneous systems. Second, we demonstrate the application of multivariate growth factor analysis to integrate consumer-generated sensory descriptors with instrumental parameters where there is no pre-existing sensory vocabulary, offering a methodological protocol adaptable to other emerging dairy regions. Such insights contribute to enhancing the valorization and improvement in local dairy production. Therefore, the aim of this study was to apply a multivariate correlation approach to analyze the physicochemical and sensory profiles of milk produced by small-holder farmers in Supe, Barranca.

2. Materials and Methods

2.1. Study Area and Sample Collection

The study was conducted in the rural community of Piedra Parada, Supe district, Barranca province, Lima department, Peru (10°50′41″ S, 77°41′14″ W, 53 m.a.s.l.). This location was selected due to its representativeness of small-scale dairy production systems in coastal Peru, where cattle farming constitutes the primary economic activity for numerous families. The region's proximity to the Pan-American Highway facilitates market access, yet producers face significant challenges related to technical assistance, infrastructure, and quality standardization. Sample collection took place on 22 January 2025, during the austral summer, when climatic conditions (ambient temperature averaging 24–26 °C) pose additional challenges for milk preservation and quality maintenance. Samples were transported under controlled conditions and analyzed at the Food Analysis Laboratory of the National University of Barranca (UNAB), which is equipped with standardized instrumentation and participates in periodic inter-laboratory quality assurance programs.

2.2. Sampling Design and Protocol

The study population consisted of members of the Cattle Breeders Association "Nuevo Progreso" of Piedra Parada, an organization comprising 11 active smallholder producers. This association was established to collectively market milk and access technical support services, yet individual production practices vary considerably due to differences in herd size (ranging from 3 to 15 lactating cows per producer), feeding strategies (pasture-based versus supplemented), milking hygiene, and cooling infrastructure availability. A non-probabilistic convenience sampling approach was employed, collecting raw milk samples from all 11 active producers present on the sampling day (coded as Dairy Farmer (DF): DF1 to DF11). This census-type approach within the association ensures comprehensive coverage of existing production variability. The sample size, while modest, is consistent with similar characterization studies in smallholder systems where intensive multivariate analysis is applied [19,23,24], as the analytical depth compensates for limited sample numbers through detailed variable measurement.

Sampling was carried out between 5:00 and 6:00 a.m., coinciding with morning milking, to capture milk at its freshest state and minimize compositional changes due to microbial activity. The protocol strictly followed the guidelines of the Peruvian Technical Standard NTP 202.112:2018 (Dairy products. Sampling. General instructions) [25]. For each producer, milk was manually homogenized in the collection container (traditional aluminum "porongo") using a sterile stainless-steel plunger to ensure fat distribution uniformity. Approximately 150 mL of milk was then aseptically transferred into sterile, food-grade polypropylene bottles with leak-proof caps; bottles were pre-labelled and opened immediately before filling to avoid contamination. Particular care was taken to prevent contact between hands and bottle interiors or caps. Each sample was uniquely coded (DF1-DF11) and immediately placed in a validated insulated container with frozen gel packs maintaining internal temperature at 2 ± 2 °C, verified by a calibrated data logger. Transport time to the laboratory was approximately 30 min [2], with continuous temperature monitoring to ensure cold chain integrity, as recommended by Moschopoulou et al. [26] and Poghossian et al. [27] for preserving raw milk composition prior to analysis. Upon laboratory arrival, samples were immediately refrigerated at 4 °C and analyzed within 4 h to prevent deterioration.

2.3. Analytical Methodology

2.3.1. Physicochemical Analysis

Physicochemical parameters were determined simultaneously using an ultrasonic milk analyzer LACTOSCAN MCC (Milkotronic Ltd., Nova Zagora, Bulgaria), which operates on the principle of differential ultrasound absorption by milk components. The parameters quantified included: fat (%), protein (%), lactose (%), non-fat solids (SNF, %), total solids (TS, %), density (g/mL), pH, titratable acidity (% lactic acid equivalent), freezing point (°C), conductivity (mS/cm), and calculated water addition (%). The instrument was calibrated prior to analysis using reference milk samples with known composition provided by the manufacturer, following the established protocol of two-point calibration with subsequent verification. Each sample was analyzed in duplicate after gentle inversion to ensure fat globule dispersion, with results expressed as mean ± standard deviation. This rapid instrumental methodology has been extensively validated against reference methods (Gerber for fat, Kjeldahl for protein) and demonstrates correlation coefficients exceeding 0.95, making it suitable for routine quality assessment and research applications [28–30]. The choice of this method balances analytical accuracy with the need for rapid, cost-effective analysis compatible with smallholder context requirements. The samples were conditioned at 23 ± 2 °C for measurement.

2.3.2. Colorimetric Analysis

Milk color was quantified using the CIEL*a*b* color space, which provides a three-dimensional representation of color perception closely correlated with human visual assessment. Measurements were performed using a portable colorimeter NH300 (3nh, Shenzhen, China) equipped with a measurement aperture of 8 mm, D65 illuminant, and 10° observer angle, following the Commission Internationale de l'Eclairage (CIE) recommendations. The instrument was calibrated before each measurement session using a standard white plate (L* = 97.83, a* = −0.43, b* = +1.98). Approximately 50 mL of milk was placed in a standardized optical glass cuvette (20 mm path length) and measured against a white background to minimize light transmission variability. The parameters evaluated were: L* (lightness, ranging from 0 = black to 100 = white), a* (green–red component, negative values indicate green, positive values red), and b* (blue–yellow component, negative values indicate blue, positive values yellow). From these primary measurements, the Whiteness Index (WI) and Yellowness Index (YI) were calculated according to standard formulas: $WI = 100 - \sqrt{[(100 - L)^2 + a^2 + b^{*2}]}$ and $YI = 142.86\ b^*/L$ [31–33]. Each sample was analyzed in triplicate with gentle swirling between measurements to account for potential fat separation, and results were expressed as mean ± standard deviation. The CIELa*b* system is internationally recognized as the standard for objective color evaluation in dairy products, enabling precise quantification of subtle color differences that influence consumer perception and product grading [34,35]. Color parameters are particularly informative in raw milk as they reflect feeding regimes (carotenoid content from pasture) and potential thermal abuse [9].

2.3.3. Sensory Analysis

The Flash Profile method was employed for sensory characterization, selected for its ability to generate rapid, reproducible sensory maps without requiring extensive panel training, making it particularly suitable for exploratory studies and product typification in resource-limited settings [15]. A panel of 11 consumers (6 female, 5 male, aged 22–45 years) was recruited from the university community based on availability, interest, and absence of known taste disorders. Panelists were selected by non-probabilistic convenience sampling, consistent with Flash Profile methodology which prioritizes individual discrimination ability over representative sampling. The panel underwent two training sessions of one hour each, conducted in a standardized sensory evaluation laboratory equipped with individual booths, controlled lighting, and temperature-controlled sample presentation (10 ± 1 °C).

In the first session, panelists were presented with the complete set of 11 milk samples, each coded with three-digit random numbers, and were instructed to individually generate a list of sensory descriptors covering appearance, odor, flavor, and texture attributes. Descriptor generation was performed freely without restrictions on terminology, allowing panelists to use their own vocabulary. In the second session (30 min later), panelists received their lists with their own vocabulary of descriptors generated in the first session and were asked to rank all the samples for each descriptor according to perceived intensity, using a rank-ordering approach. This ranking procedure eliminates scaling biases and focuses on comparative discrimination. Samples were presented simultaneously in randomized order, with water and unsalted crackers provided for palate cleansing between evaluations. Panelists were allowed to re-taste samples as needed to confirm rankings. The complete session lasted approximately 90 min, with mandatory breaks to prevent sensory fatigue. This methodology has been successfully applied to various dairy products, demonstrating good discrimination ability and reproducibility [36].

2.4. Statistical Analysis

Statistical analysis was performed using R software (version 4.3.1) with the FactoMineR and SensoMineR packages, complemented by XLSTAT version 2023 (Addinsoft, New York, NY, USA) for specific multivariate procedures. Descriptive statistics (mean and standard deviation) were calculated for all physicochemical and colorimetric variables. Normality was assessed using the Shapiro–Wilk test, and homogeneity of variances was verified with Levene's test. When assumptions were met, one-way analysis of variance (ANOVA) was applied to detect significant differences among producers, followed by Tukey's Honestly Significant Difference (HSD) post hoc test for multiple comparisons. Statistical significance was set at $p < 0.05$. Sensory data from the Flash Profile (individual panelist rankings for each descriptor across all samples) were analyzed using Generalized Procrustes Analysis (GPA). GPA is specifically designed to compare configurations from different assessors by applying translations, rotations, and scaling transformations to achieve a consensus configuration that maximizes agreement while preserving individual differences [36]. The analysis generated a consensus sensory space where samples are positioned based on their average sensory profiles, along with the contribution of each descriptor to the principal dimensions. The quality of the consensus was assessed through the percentage of variance explained and the residual per panelist. To integrate the physicochemical, colorimetric, and sensory datasets, Hierarchical Multiple Factor Analysis (HMFA) was performed. HMFA extends Multiple Factor Analysis by accommodating hierarchical structures in the data, here defined at two levels: (i) the base variables (individual physicochemical measurements, color coordinates, sensory descriptors), and (ii) the groups (physicochemical parameters, sensory profile) [13]. This method balances the influence of each group regardless of the number of variables they contain, enabling fair comparison between instrumental and sensory data. The analysis generated factor maps showing sample positions in the consensus space and partial axes representations showing the contribution of each group to the positioning of each sample. The integration of univariate and multivariate analyses enables comprehensive characterization by capturing the complex interrelationships inherent in milk quality assessment, allowing a holistic understanding through diverse data integration [3,11].

3. Results and Discussion

3.1. Physicochemical Parameters

The physicochemical composition of raw milk from the 11 producers (DF1–DF11) showed significant variability ($p < 0.05$) across most evaluated parameters (Table 1), suggesting substantial differences in herd management, feeding practices, and potential manipulation among producers.

Table 1. Physicochemical characterization of raw milk from small producers.

Dairy Farmer	Fat (%)	Non-Fatty Solids (%)	Density (g/mL)	Lactose (%)	Salts (%)	Protein (%)	Freezing Point (°C)	Water Addition (%)	Total Solids (%)	pH	Conductivity (mS/cm)
DF1	3.01 ± 0.03 cd	8.22 ± 0.04 a	1.0285 ± 0.14 bc	**4.52 ± 0.02 a**	**0.67 ± 0.01 a**	**3.01 ± 0.01 a**	−0.52 ± 0.01 de	**0.32 ± 0.39 d**	11.23 ± 0.04 b	6.81 ± 0.03 b	**4.45 ± 0.15 d**
DF2	3.00 ± 0.01 cd	7.84 ± 0.06 b	**1.0301 ± 0.23 a**	4.32 ± 0.04 b	0.65 ± 0.01 b	2.89 ± 0.02 b	−0.48 ± 0.01 c	8.13 ± 0.87 c	7.84 ± 0.06 f	**6.74 ± 0.02 d**	5.02 ± 0.11 c
DF3	**2.88 ± 0.08 d**	8.17 ± 0.03 a	1.0284 ± 0.09 bc	**4.49 ± 0.02 a**	**0.66 ± 0.01 a**	**2.99 ± 0.01 a**	−0.51 ± 0.02 d	**1.15 ± 0.51 d**	11.05 ± 0.10 b	6.81 ± 0.02 b	4.75 ± 0.06 cd
DF4	**2.83 ± 0.04 d**	7.32 ± 0.07 cd	**1.0253 ± 0.23 g**	4.02 ± 0.04 cd	**0.59 ± 0.01 d**	2.67 ± 0.02 ef	−0.46 ± 0.04 b	12.37 ± 0.89 b	10.15 ± 0.10 c	6.81 ± 0.01 b	5.52 ± 0.26 ab
DF5	3.79 ± 0.04 ab	7.46 ± 0.05 c	1.0276 ± 0.13 ef	4.10 ± 0.02 c	0.61 ± 0.02 c	2.74 ± 0.02 d	−0.46 ± 0.03 b	12.30 ± 0.67 b	8.25 ± 0.08 e	6.76 ± 0.01 cd	5.10 ± 0.13 bc
DF6	**2.88 ± 0.03 d**	**8.30 ± 0.04 a**	1.0289 ± 0.10 b	**4.56 ± 0.02 a**	**0.67 ± 0.03 a**	**3.04 ± 0.01 a**	−0.52 ± 0.02 de	**0.01 ± 0.01 d**	11.18 ± 0.06 b	6.78 ± 0.01 bc	4.97 ± 0.18 c
DF7	**4.06 ± 0.12 a**	**8.28 ± 0.12 a**	1.0279 ± 0.36 de	**4.55 ± 0.07 a**	**0.67 ± 0.01 a**	**3.02 ± 0.04 a**	−0.53 ± 0.08 e	**0.06 ± 0.11 d**	**12.34 ± 0.22 a**	6.77 ± 0.01 cd	4.96 ± 0.05 c
DF8	3.12 ± 0.03 cd	7.43 ± 0.03 c	1.0272 ± 0.11 f	4.08 ± 0.02 c	0.61 ± 0.01 c	2.73 ± 0.01 de	−0.46 ± 0.02 b	12.43 ± 0.48 b	8.55 ± 0.06 e	**6.87 ± 0.01 a**	**5.65 ± 0.08 a**
DF9	3.13 ± 0.03 cd	**7.20 ± 0.04 d**	1.0271 ± 0.10 f	**3.96 ± 0.02 d**	**0.59 ± 0.02 d**	**2.65 ± 0.02 f**	**−0.44 ± 0.02 a**	**16.15 ± 0.51 a**	**7.33 ± 0.07 g**	6.79 ± 0.01 bc	**5.71 ± 0.25 a**
DF10	3.39 ± 0.46 bc	7.71 ± 0.08 b	1.0274 ± 0.18 ef	4.24 ± 0.05 b	0.63 ± 0.01 b	2.83 ± 0.03 c	−0.48 ± 0.06 c	7.88 ± 1.17 c	9.77 ± 0.23 d	6.77 ± 0.02 cd	4.99 ± 0.16 c
DF11	3.77 ± 0.03 ab	**8.29 ± 0.04 a**	1.0281 ± 0.14 cd	**4.55 ± 0.02 a**	**0.67 ± 0.01 a**	**3.03 ± 0.02 a**	**−0.53 ± 0.02 e**	**0.01 ± 0.01 d**	**12.06 ± 0.07 a**	6.78 ± 0.02 bcd	**4.70 ± 0.16 cd**

Note: Values are presented as mean ± standard deviation and different letters in the same column indicate significant differences ($p < 0.05$). Color highlighted in black indicates higher value and in red lower value.

Fat content showed significant differences, with recorded values ranging from 2.83 to 4.06%. DF4, DF3, and DF6 values were slightly lower; however, the remaining observed values were within the typical range for raw milk (>3.0%) [2]. The variability of this parameter directly impacts the commercial value of milk, cheese yield, and the sensory properties of derived dairy products. Lower values in bovine milk suggest a possible intentional manipulation [10]. Marked differences were also observed in solids-not-fat (SNF) and protein. DF1, DF3, DF6, DF7, and DF11 presented the highest and statistically similar values of SNF (≥8.17%) and protein (≥2.99%), which are associated with good compositional quality. In contrast, DF4, DF5, DF8, and DF9 showed the lowest SNF (≤7.46%) and protein (≤2.74%) levels. SNF values below 8.5% are generally considered substandard and may reflect poor animal nutrition or dilution with water [1].

Freezing point and water addition percentage were strongly correlated. The freezing point of pure milk is relatively constant (approximately −0.522 °C to −0.540 °C), and deviations toward less negative values are widely recognized as indicators of possible adulteration with water [37,38]. This pattern was observed in DF9 (−0.44 °C) and in DF4, DF5, and DF8 (−0.46 °C), which corresponded to the highest calculated percentages of water added (16.15, 12.37, 12.30, and 12.43%, respectively). In contrast, DF1, DF6, DF7, and DF11, with freezing points between −0.52 °C and −0.53 °C, showed a water addition close to 0%, suggesting sample purity. Although freezing point depression is commonly used as a standard indicator to detect the addition of water, confirmatory analyses (e.g., cryoscopic determination using reference standards) are necessary to validate this condition. The results obtained may suggest possible product manipulation [7,28].

Density also correlated as expected with composition. Samples with high fat and SNF (e.g., DF1, DF6, DF7) presented higher densities (≥1.028.55 g/mL), whereas adulterated samples (e.g., DF4, DF9) exhibited the lowest values (1.025.27 and 1.027.12 g/mL), reflecting the dilution effect of added water. pH remained within a narrow range (6.74–6.87) for most samples, suggesting no advanced acidification due to microbial growth at the time of analysis. However, the slightly lower pH of DF2 (6.74) could indicate early microbial spoilage [11].

Electrical conductivity showed significant variation. Lower values (e.g., DF1, DF11) were associated with normal milk composition, whereas higher conductivity (e.g., DF8, DF9) may indicate subclinical mastitis, as mammary inflammation increases epithelial permeability, allowing sodium and chloride ions to pass into the milk [7].

Based on physicochemical profiles, producers could be classified into two groups: (i) suppliers of high-quality, unmanipulated milk (DF1, DF3, DF6, DF7, DF11), and (ii) those with possible manipulation and/or low compositional quality (DF2, DF4, DF5, DF8, DF9, DF10). This heterogeneity highlights the urgent need to implement quality control systems and good milking practices within the association.

3.2. Colorimetric Parameters

Colorimetric analysis in the CIELab* space revealed significant differences ($p < 0.05$) among producers (Figure 1), directly related to physicochemical variations.

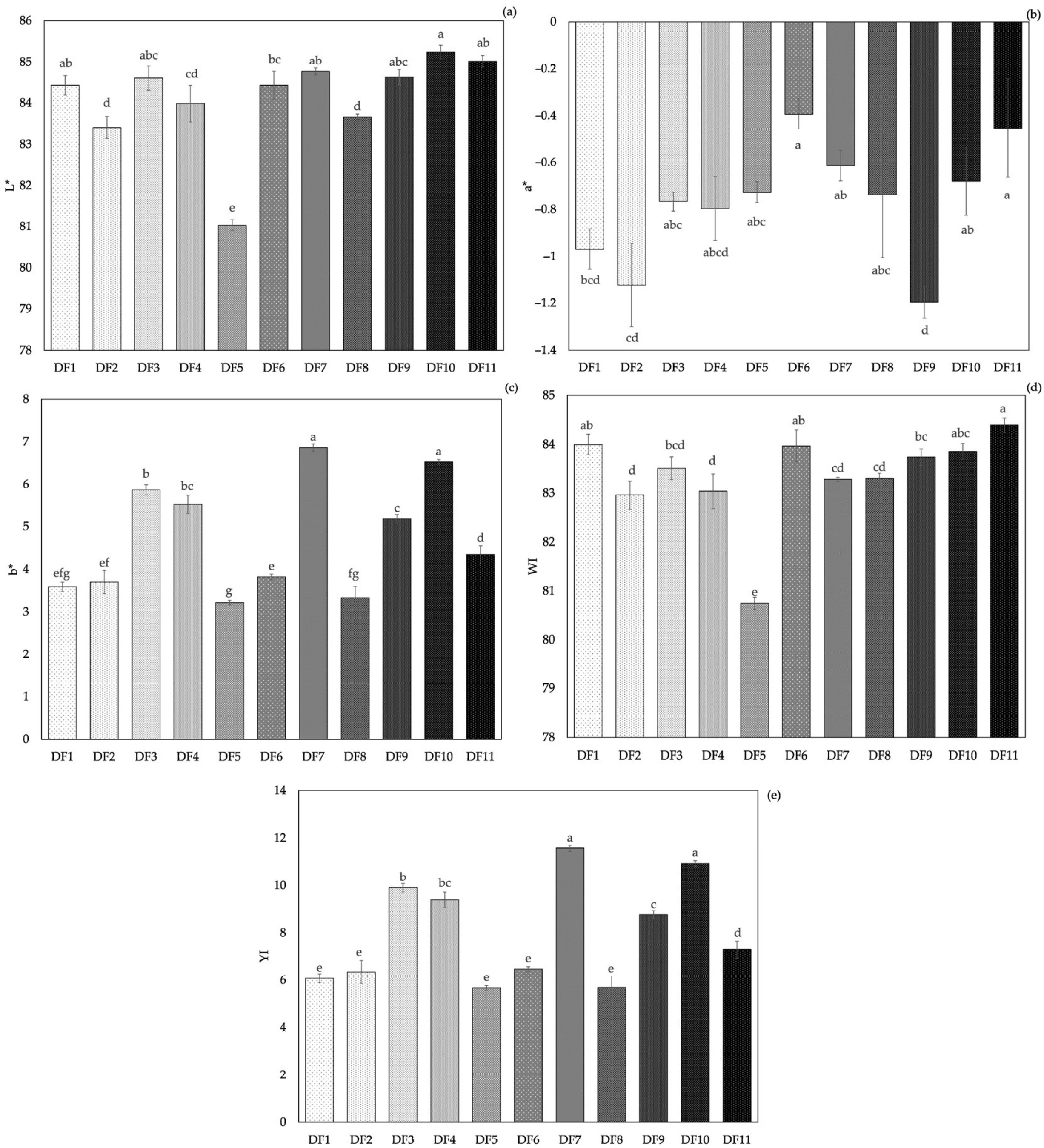

Figure 1. CIEL*a*b* colorimetric parameters of raw milk samples: Lightness (L*) (**a**), chromatic a* (**b**), chromatic b* (**c**), whiteness index (WI) (**d**), and yellowness index (YI) (**e**). (Note: Different letters for the same parameter indicate significant differences ($p < 0.05$) between producers).

Lightness (L*) ranged from 81.03 (DF5) to 85.24 (DF10). Higher L* values indicate whiter and brighter milk. DF5 showed the lowest L* value, consistent with its low fat (0.79%) and total solids (8.25%) content (Figure 1a). Fat globules scatter light, contributing to milk's opacity and whiteness [39]. In contrast, DF7 (4.06% fat) and DF11 (3.77% fat) displayed high L* values (84.77 and 85.02), confirming this relationship.

The a* coordinate (red–green axis) was negative for all samples (Figure 1b), as expected for milk, indicating a slight predominance of the green component. Although statistically significant, the small variations lack practical visual relevance. The b* coordinate (yellow–blue axis) exhibited the greatest variability (Figure 1c), ranging from 3.22 (DF5) to 6.86 (DF7). This parameter is primarily influenced by the carotenoid content (e.g., β-carotene) derived from the feed [3]. The higher b* values in DF7 and DF10 (6.86 and 6.52) suggest a diet rich in fresh forage, based on corn stover, elephant grass, and ground corn concentrate, bran, soybean meal, calcium carbonate, and mineral salts. This direct feeding confirms this relationship. Conversely, the lower b* values in DF1, DF2, DF5, DF6, and DF8 (<3.83) indicate diets based on concentrates or hay with reduced carotenoid intake. The yellowness index was directly correlated with b*, also reaching its maximum in DF7 and DF10 (Figure 1e).

From a market perspective, color plays an important role in consumer perception and product valuation in the study region. Locally, milk with a pronounced yellowish hue (higher b*) is often associated with "natural" milk production from grass-fed cows and can command a higher price. Conversely, excessively white milk can raise suspicions of adulteration or intensive feeding with concentrates, which could reduce consumer confidence. Therefore, color parameters not only serve as indicators of feeding practices, but also have implications for market positioning and quality communication strategies aimed at enhancing the value of locally produced milk.

The whiteness index (WI) reached its highest value in DF11 (84.39) (Figure 1d), consistent with its high fat and solids content and moderate yellowness (b* = 4.34). DF5 had the lowest WI (80.75), aligned with its low L* and solids. Interestingly, DF7 and DF10 both showed high b* values, but DF10 had a slightly higher WI, suggesting that an optimal combination of high L* and moderate yellowness contributes to milk being perceived as more attractive [34].

Thus, colorimetric data not only describe appearance but also serve as indirect biomarkers of diet and milk composition. The strong correlation between high b* values and pasture-based diets, as reported in the literature [39], supports the hypothesis that feeding practices among producers are a key determinant of milk quality and sensory attributes.

3.3. Sensory Profile

Generalized Procrustes Analysis (GPA) applied to Flash Profile data yielded a consensus configuration representing panelists' global sensory perception and sample–descriptor relationships (Figure 2). The first two GPA dimensions (D1 and D2) explained 66.94% of the total variance, indicating a robust representation of the sensory space [40].

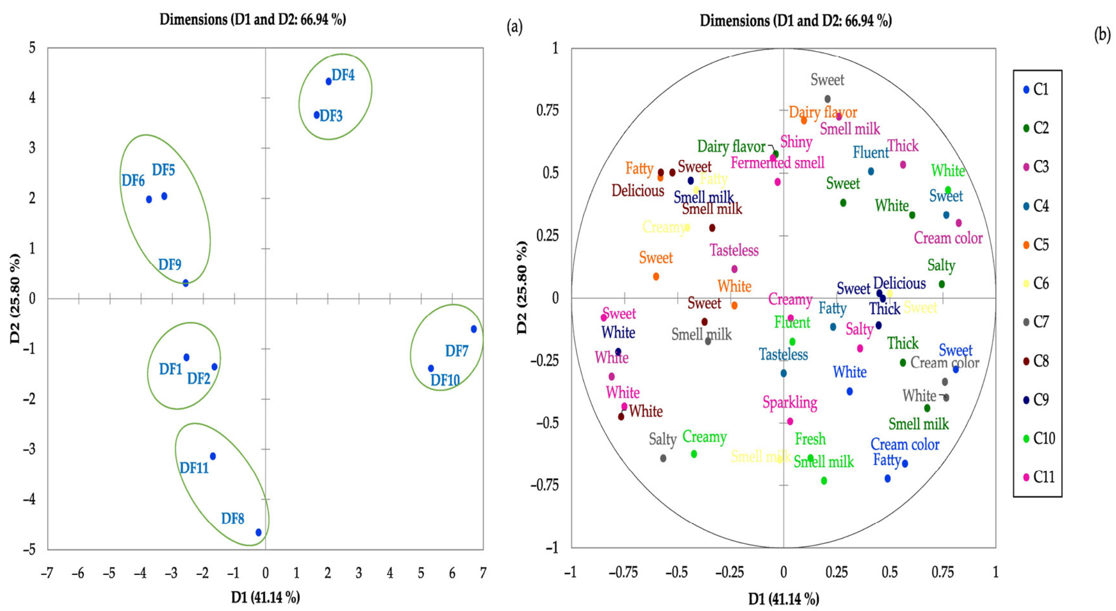

Figure 2. Generalized Procrustes analysis of the sensory profile: consensus configuration of dairy farm producers (**a**) and descriptors (**b**).

In the consensus map (Figure 2a), DF7 and DF10 clustered in the upper-right quadrant, characterized by descriptors such as Creamy, Fatty, and White–creamy. These sensory perceptions aligned with instrumental data, as these samples showed the highest fat content (4.06% and 2.06%) and elevated yellowness (b*). This consistency validates panelists' ability to capture key compositional differences [41].

Conversely, DF4, DF5, DF8, and DF9 grouped in the lower-left quadrant, consistently described as Tasteless and Salty. The "tasteless" perception reflects dilution of milk solids, consistent with the high-water addition percentages (12–16%) observed. The "salty" attribute is linked to subclinical mastitis, as increased mammary permeability elevates sodium chloride levels, which correlates with the high electrical conductivity observed in DF8 and DF9 [42]. The remaining samples (DF1, DF2, DF3, DF6, DF11) occupied central positions, associated with milder positive attributes such as Sweet-milk odor and Sweet-white. DF11, positioned closer to the high-quality cluster, also showed optimal composition (high fat and protein, no adulteration), reinforcing consistency between instrumental and sensory data.

The descriptor vector map (Figure 2b) indicated that the first axis (F1, 41.14%) represented a quality and flavor gradient: positive values correlated with Fatty, Creamy, White, and Delicious–sweet attributes, while negative values aligned with Tasteless and Salty. The second axis (F2) appeared to capture subtler differences, likely related to whiteness intensity and fluidity. Overall, sensory differences among producers were primarily driven by water adulteration and fat content [43].

3.4. Hierarchical Multiple Factor Analysis (HMFA)

HMFA was applied to integrate the physicochemical and sensory variable groups, providing a comprehensive framework for understanding how both domains converge to define overall milk quality (Figure 3). The first two axes of HMFA (D1 and D2) explained 45.31% of the total variance (D1: 25.16%; D2: 20.15%), offering a robust representation of the underlying multivariate relationships [13].

The representation of variable groups (Figure 3a) shows close proximity between the physicochemical and sensory parameter vectors, indicating strong positive correlation and good alignment between instrumental measurements and sensory perception. The individual factor map (Figure 3b) revealed a clear separation of producers into three distinct clusters. The first cluster, located in the lower right quadrant, comprised DF1, DF6, and DF11. The second cluster, spanning the lower and upper left quadrants, included DF2, DF5, DF8, and DF9. The third cluster, positioned in the upper right quadrant, consisted of DF3, DF4, DF7, and DF10. The partial cloud representation (Figure 3c) illustrates the similarity of response generated by the physicochemical and sensory parameters for each producer. Producer DF7 exhibited notable variability in its results, indicating some discordance between instrumental and sensory evaluations. Similar but less pronounced discordance was observed for DF5, DF9, and DF10. In contrast, the remaining producers showed highly concordant results across both parameter groups, demonstrating strong alignment between measured composition and perceived sensory attributes.

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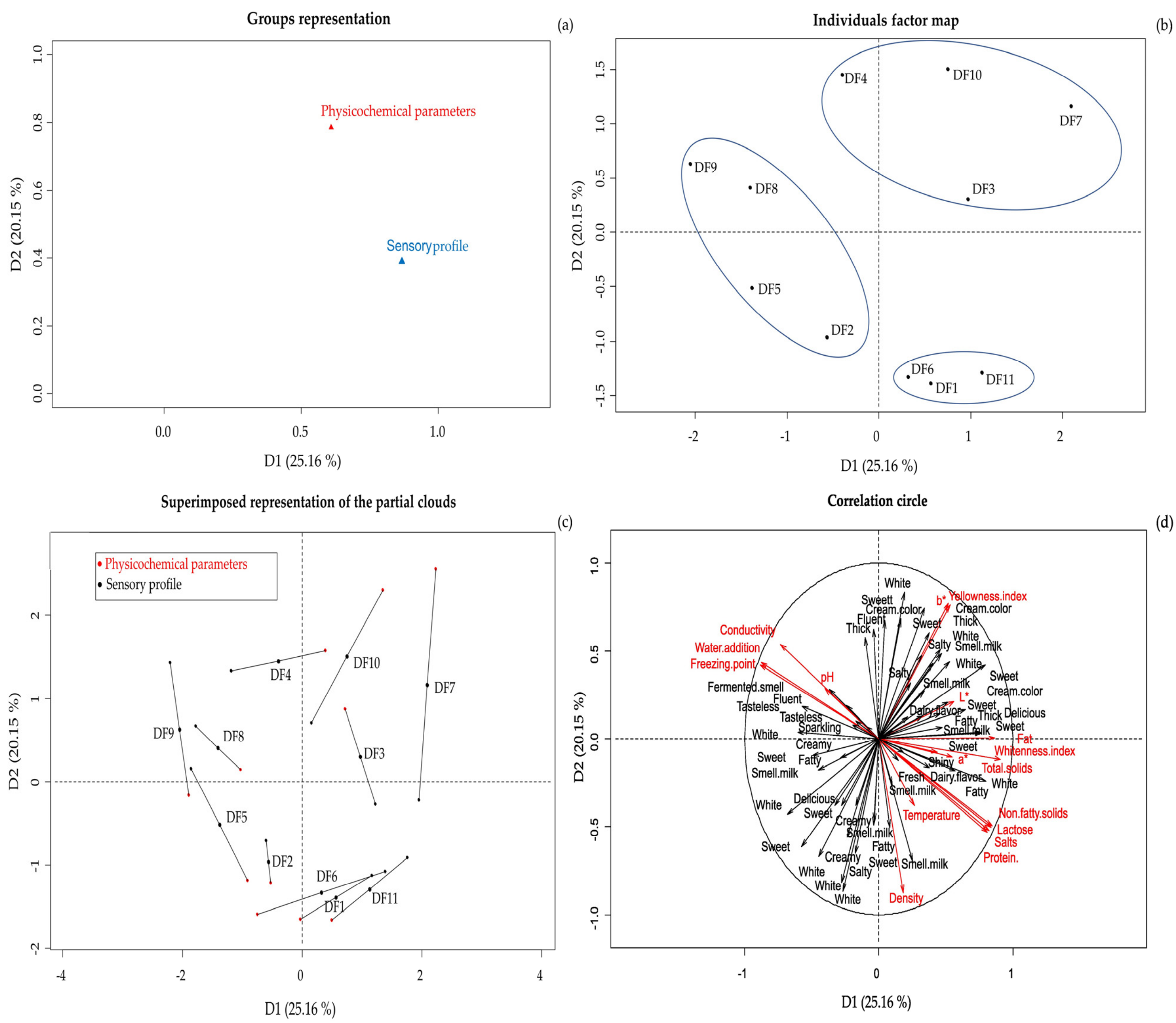

Figure 3. Multivariate integration using Hierarchical Multiple Factor Analysis: representation map of physicochemical and sensory methods (**a**), consensus map of producers (**b**), comparison map of samples by methods (**c**), and correlation between physicochemical parameters (red color) and sensory profile (black color) (**d**).

The correlation between physicochemical parameters and sensory attributes (Figure 3d) further elucidates producer positioning. For the high-quality producers (DF3, DF4, DF7, DF10), both physicochemical and sensory vectors pointed consistently in the same direction, reflecting strong concordance: elevated fat content corresponded directly with sensory descriptors such as "fatty" and "creamy." For the low-quality producers (DF2, DF5, DF8, DF9), both datasets converged negatively, aligning water adulteration indicators (elevated freezing point, low conductivity, high calculated water addition) with unfavorable sensory profiles ("tasteless," "salty"). Producers DF1, DF6, and DF11 presented an intermediate pattern: although their physicochemical profile resembled that of the high-quality group, their sensory profile lacked comparably intense fatty and creamy descriptors, resulting in a more central position in the consensus space.

Overall, HMFA confirmed that milk quality is defined by the synergy and/or discordance between compositional integrity and sensory perception. This analysis identified DF7 and DF10 as producers of the highest-quality milk. Furthermore, it revealed that manipulation through the addition of water is the critical factor that leads to low quality, both instrumentally and sensorially [44,45].

Based on the results of this research conducted with small-scale producers in Supe and Barranca, a replicable template for integrated milk quality assessment is offered, applicable to small-scale dairy systems in other developing regions. The sequential approach, which combines univariate analysis (freezing point for detecting possible manipulation or adulteration), colorimetric characterization (CIEL*a*b* for inferring feeding regimes), Generalized Procrustes Analysis for sensory consensus, and Hierarchical Multifactor Factor Analysis for correlation, can be easily adapted to diverse production contexts. Its reliance on portable and cost-effective instrumentation (ultrasonic milk analyzer, portable colorimeter) and a rapid, consumer-based profiling methodology makes it suitable for resource-constrained environments where access to conventional quality control laboratories and trained descriptive panels is limited. By establishing correlations between rapid instrumental measurements and sensory outcomes, this approach enables producer associations and cooperatives to implement quality monitoring programs, develop quality-based payment systems, and design targeted technical assistance interventions without requiring infrastructure investment. Future applications in other regions may further validate and refine this information under diverse agroecological conditions, livestock genetics, and cultural consumption patterns.

4. Conclusions

This study established a robust multivariate correlation between instrumental and sensory parameters of raw milk produced by the smallholder association in Supe, Barranca. The results clearly identified two contrasting groups: high-quality milk producers (DF7, DF10, DF11), characterized by elevated fat content (>3.77%), total solids (>12.06%), and a "fatty/creamy" sensory profile; versus producers supplying possible manipulation or adulterated milk (12–16% water addition) with a "tasteless/salty" profile (DF4, DF5, DF8, DF9). HMFA confirmed a significant concordance between both datasets, highlighting water adulteration and fat content as the main determinants of qualitative variability. The practical implications are immediate and substantial. These findings provide a solid technical basis for implementing a quality-based payment system that incentivizes optimal milk production, alongside training programs in good milking and sanitary practices. Moreover, the applied methodology proved to be an effective model for comprehensive evaluation in smallholder systems, simultaneously offering a diagnostic tool for decision-making and an analytical framework replicable in similar contexts. Ultimately, this contributes to the valorization and competitive improvement in the local dairy chain.

5. Limitations

This study is based on a single sampling (22 January 2025) with the voluntary participation of 11 producers, which limits the generalizability of the results. Milk composition exhibits considerable temporal variability due to seasonal changes in feed availability, weather conditions, and lactation stages—factors that could not be recorded at a single point in time. Furthermore, this cohort represents only producers affiliated with a single association and may not reflect the diversity of smallholder dairy systems in Barranca or the Peruvian coast. Future studies should incorporate microbiological assessment to provide a complete quality profile, longitudinal sampling across seasons and extend to multiple producer associations to validate these findings and establish robust quality baselines.

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