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RESEARCH ARTICLE
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Evaluating Physical and Chemical Quality of Corn Kernel as Poultry Feed Ingredient in the Procurement of Feed Mill Raw Material

Jasmal Ahmari Syamsu [1,2,*], Sri Purwanti [1], Abdul Alim Yamin [1], Ichlasul Amal [3] and Anjas Asmara Samsudin [4,5]

[1]Faculty of Animal Science, Universitas Hasanuddin, Makassar, Indonesia 90245
[2]Center of Research and Development for Livestock Resources and Tropical Animal, Universitas Hasanuddin, Makassar, Indonesia 90245
[3]Faculty of Vocational Studies, Universitas Hasanuddin, Makassar, Indonesia 90245
[4]Institute of Tropical Agriculture and Food Security (ITAFoS), Universiti Putra Malaysia, Serdang, Selangor Malaysia 43400
[5]Department of Animal Science, Faculty of Agriculture, Universiti Putra Malaysia, Serdang, Selangor Malaysia 43400
*Corresponding author: jasmal.syamsu@unhas.ac.id

ABSTRACT

This study evaluates the physical and chemical quality of corn kernels supplied to a feed mill in South Sulawesi, Indonesia, focusing on identifying key parameters affecting feed safety and quality. A total of 1,781 corn batches were analyzed for physical quality parameters, including moisture content (Mc), damaged kernels (Dk), moldy kernels (Mk), broken kernels (Bk), and foreign materials (Fm), based on SNI-8926 2020 standards. Chemical quality was assessed through proximate analysis of 60 randomly selected samples, measuring ash content, crude protein, crude fat, crude fiber, calcium (Ca), and phosphorus (P). Descriptive analysis showed an average Mc of 26.5±5.42%, Dk 1.02±0.63%, Mk 1.78±1.17%, Bk 1.12±0.44%, and Fm 0.86±0.29%. Chemical parameters exhibited significant variability, with crude fat and ash content showing the widest ranges. High moisture content, which frequently exceeded SNI thresholds, emerged as the primary challenge, creating conditions conducive to mold growth and increasing the risk of mycotoxin contamination. While most physical quality indicators, such as Dk, Fm, and Bk, largely met premium and medium-grade standards, Mc variability was a critical concern. This study highlights the need for improved drying and handling practices to mitigate moisture-related issues in corn quality. Based on a single feed mill in South Sulawesi, the findings provide insights into regional corn quality challenges and underscore the importance of stricter adherence to quality standards to ensure feed safety and integrity.

Keywords: Corn Kernel, Feed Ingredient, Feed Mill, Physical Quality, Poultry.

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INTRODUCTION

Corn is vital to Indonesia's economy, ranking as the country's second most important food crop after rice. Indonesia's harvest area contributes 2.42% to the global crop harvesting areas. In 2023, Indonesia produced 14 million tons of corn across a harvest area of 2.4 million hectares. South Sulawesi is one of Indonesia's 11 major maize-producing regions, contributing an average of 7.6% to the country's total production annually. In the same year, South Sulawesi produced approximately 1.1 million tons of corn from a harvest area of 181.8 thousand hectares (BPS, 2024). Of the total corn production, 55% was used for animal feed, 30% for food consumption, and 15% for industrial purposes and seed production. There are 110 animal feed mills in Indonesia, operated by 44 companies and distributed across 10 provinces. 2023 South Sulawesi was home to seven feed mills, collectively producing approximately 1,188 million metric tons of feed (USDA, 2023).

The utilization of corn in animal feed plays a crucial role in enhancing production efficiency and feed quality. This influence stems from the substantial proportion of corn incorporated into feed formulations. For instance, corn

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constitutes approximately 50% of the ration formulation for laying hens, 35-45% for broilers, and 50-55% for poultry breeders (Auza et al., 2021; Auza et al., 2023). To ensure the suitability of corn as a raw material for the feed industry, rigorous examination processes are conducted, encompassing both physical properties and laboratory analysis (Rodrigues et al., 2014; Koeshardianto et al., 2023). Feed mill companies in South Sulawesi implement stringent quality control procedures, conducting inspections upon the arrival of new corn shipments transported by truck from suppliers at receiving docks. Corn batches are sourced from smallholder farmers across various regions within and outside the province of South Sulawesi, resulting in various conditions and quality. (Fajar et al., 2021). Corn quality parameter examination follows the Indonesian National Standard (SNI-8926 2020), such as moisture content, damaged kernel, moldy kernel, broken kernel, and foreign maerial. Based on these parameters, corn kernels are classified into three quality levels: Premium, Medium I, and Medium II (BSN, 2020).

Generally, farmers employ conventional farming practices, particularly in crop management aspects such as shelling, drying, and storage (Cecil et al., 2023). Corn shelling is typically done using locally produced sheller machines that are often unstandardized and untested. The drying process involves spreading the corn on tarps and leaving it to dry in the sun for two to three days. Consequently, the moisture content of the corn is highly dependent on weather conditions during drying. This traditional drying and storage method can lead to significant contamination of the corn kernels and post-harvest losses (Bendinelli et al., 2020).

Feed mills must carefully adjust the quality of low-grade corn to meet factory feed formulation standards. A key factor affecting feed quality is moisture content, which recommends maintaining moisture levels between 14% and 16% (Cabañas-Ojeda et al., 2023). Corn with moisture levels exceeding 16% is prone to quality degradation, storage damage, and increased risk of fungal contamination. Damaged kernels, including moldy or cracked seeds, are particularly vulnerable to contamination by destructive microorganisms such as fungi (Islam et al., 2018). These contaminants can lead to mycotoxins, such as deoxynivalenol and zearalenone, negatively affecting feed safety. No significant difference in energy and nutrient content between clean and uncleaned corn (Yoder et al., 2021). However, Hagen et al. (2020) found that cracked kernels had higher concentrations of deoxynivalenol and zearalenone, emphasizing their susceptibility to mycotoxin contamination. Interestingly, corn batches with broken kernels and foreign material of 7.9% showed reduced mycotoxin levels. This finding suggests that the extent of contamination is influenced by kernel damage and other factors, such as the composition of foreign material or the distribution of fungal exposure within the batch. Broken kernels are highly susceptible to fungal contamination, and damage of up to 10% can significantly increase moldy growth (Fan et al., 2024).

The decrease in corn quality, which adversely affects production efficiency in feed mills, inevitably impacts farmers or corn suppliers (Arifin et al., 2024). Farmers may resort to selling corn at a lower price to offset the decline in production efficiency. At the producer level, the price of corn can fluctuate by approximately 16% based on the moisture content; notably, low-quality corn (humidity ≥30%) may be purchased at around 29% lower than the standard price (USDA, 2023). Remarkably, more than 97% of corn received by feed mills falls below the Indonesian National Standard (SNI) quality requirements (Fajar et al., 2021). This study aims to assess the screening qualities of corn kernels received by feed mills and to identify the key parameters that prevent most of these batches from meeting SNI standards. The findings from this assessment will be instrumental in prioritizing future corn-handling practices at the producer level.

MATERIALS & METHODS

Sample Description

The research was conducted at a feed mill company in Makassar, South Sulawesi, Indonesia. Corn suppliers delivering to the mill come from various regions across Sulawesi Island. However, this study focuses exclusively on samples from South Sulawesi (Fig. 1). Corn kernel transportation to the company is highly intensive, with approximately 40 to 70 trucks arriving daily, each carrying 9 to 10 tons of corn. Suppliers typically source the corn from middlemen in corn-producing villages or directly from farmers across South Sulawesi. The trucks are medium-sized with open beds covered by tarps, lacking specialized equipment or technology. Due to the diverse origins and basic transport methods, the corn is exposed to various environmental factors during storage and transit, making it highly susceptible to quality degradation. Given this variability, the company implements strict standard procedures for assessing the quality of incoming corn. Upon arrival, each truck undergoes a physical inspection, which forms the basis for determining the price. The price is then negotiated with the suppliers. Once agreed, the trucks proceed to the weighbridge to determine the exact quantity of corn delivered. Following the physical inspection, the company carries out additional processes to ensure that the corn used in feed production meets uniform quality standards.

Sampling

The data collection in this study followed the company's established procedures. A total of 1,781 samples were collected over three months, with sampling conducted four times per month. Daily samples were taken randomly, with approximately 150 samples collected per batch of corn as trucks arrived at the warehouse. For each truckload, samples were taken from the container's top, middle, and bottom sections, with 250g from each section, and the average values were used for each research replicate. The transportation date and the origin of the corn kernels were also documented. For proximate analysis, 60 samples were randomly selected from the batches.

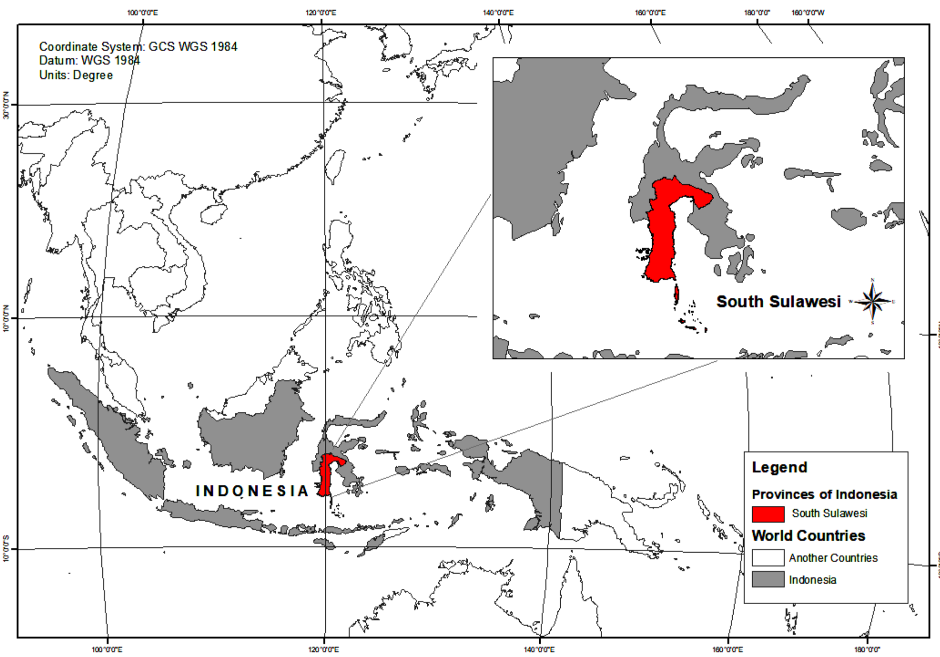

Fig. 1: Map of Indonesia showing South Sulawesi Province (Source: Geospatial Information Agency of Indonesia. (2024). Administrative Boundaries Map of Indonesia [Map]. Retrieved from https://satupeta.go.id).

Chemical quality inspections were conducted on corn that was ready to be used as raw feed material. Random sampling for chemical quality testing was performed daily during the study period, with five sample units collected per session, resulting in 60 units.

Physical Quality Measurement

The parameters and methods for measuring the physical quality included moisture contents, damaged kernel, moldy kernel, broken kernel, and foreign maerial.

a. Moisture content (Mc) was obtained using the Grain Moisture Tester model PM-650. About 100g samples were taken from three key sections of the stack: the surface (top), middle and bottom. The process began with mounting the funnel securely onto the manual hopper and fed until it reached one-third of its depth. The funnel was removed to level the sample and eliminate excess material. Subsequently, the sample was carefully transferred from the manual hopper to the center of the measuring unit at a consistent speed, ensuring complete loading within 5 to 6 seconds. Following this loading phase, a brief waiting period ensued, during which the decimal point blinked for approximately 5 seconds. Finally, the device promptly displayed the measuring count and moisture content, concluding the measurement process.

b. Physical Quality. The physical quality measurement procedure, namely damaged kernel, moldy kernel, broken kernel, and foreign maerial, refers to the measurement method specified in SNI-8926.2020-Corn (BSN, 2020). Corn kernels in normal conditions, as in Fig. 2A.

c. The physical quality measurement procedure is as follows:

- Damage kernel (Dk) refers to whole or broken kernels that have been adversely affected by mechanical, biological, physical, and enzymatic factors. The process involves visually inspecting damaged seeds by isolating them from good kernels. The necessary equipment includes aluminum foil, tweezers, a scale (0.01g accuracy), and a magnifying glass. A sample weighing 250g is initially examined using a handheld magnifying glass over aluminum foil. Broken seeds, identifiable by specific visual characteristics (as depicted in Fig. 2B), are meticulously separated from intact corn kernels using tweezers. The weight of the separated damaged seeds (referred to as Dw) is then measured. Subsequently, the percentage of damaged seeds (Bs) was calculated using the following equation:

$$Dk\ (\%) = \frac{Dw}{250} \times 100$$

- Moldy kernels (Mk) were corn kernels that had been affected by fungus, resulting in a change in color from their original appearance. The moldy kernels were separated by visual identification under ultraviolet (UV) light. 250g of the sample was spread onto aluminum foil, revealing corn kernels that fluoresced under UV light (Fig. 2C). Moldy kernels were meticulously identified and separated from the batch using tweezers. The percentage of mold kernels was calculated by dividing the weight of moldy kernels in the sample by the total weight of the sample and multiplying by 100:

$$Mk\ (\%) = \frac{Mw}{250} \times 100$$

- Broken kernel (Bk): corn kernels that were broken during the processing process and had a minimum size of 0.6 parts of whole corn kernel (Fig. 2D). Separating broken kernels was performed visually using tweezers and a handheld magnifying glass. The percentage of broken kernels was calculated by dividing the weight of broken kernels (Bw) by the total sample weight and multiplying by 100:

$$Bk\ (\%) = \frac{Bw}{250} \times 100$$

- Foreign material (Fm). The separation of foreign objects (Fig. 2E) by visually identifying and isolating foreign material using tweezers and a magnifying glass. The percentage of foreign material was calculated by dividing the weight of foreign material in the sample by the total weight of the sample and multiplying by 100:

$$Fm\ (\%) = \frac{Fw}{250} \times 100$$

The value of each parameter in determining the quality class of Premium (P), Medium I (MI), and Medium II (MII) refers to the quality requirements specified in SNI-8926.2020 (Table 1), all samples with parameter values higher than the MII class are further categorized as non-category (NC).

Fig. 2: Physical corn kernel pictures, A=normal; B=damage kernels; C=moldy kernels; D=broken kernels; and E=foreign materials.

Table 1: Corn moisture and physical quality standards for animal feed as per SNI-8926.2020

Parameters	Unit	Classes		
		Premium	Medium-I	Medium-II
Moisture content (Mc)	%	14	14	16
Damage Kernel (Dk)	%	3	5	7
Moldy Kernel (Mk)	%	1	2	4
Broken Kernel (Bk)	%	1	5	8
Foreign material (Fm)	%	1	2	2

Chemical Quality

The chemical analysis of the corn aimed to assess its quality as a raw material for feed ingredients. Key parameters measured included proximate values such as contents ash, crude protein, crude fat, crude fiber, calcium, and phosphorus. Laboratory testing was conducted using the AOAC Official Method (AOAC, 2019), ensuring accuracy and adherence to established feed ingredient quality assessment standards. Ash content is measured by incinerating the sample at 550°C and weighing the remaining minerals. Crude protein is calculated from nitrogen content obtained through distillation and titration multiplied by 6.25. Crude fat is extracted using ether in a Soxhlet apparatus, and the residue is weighed. Crude fiber is analyzed by boiling the sample in acid and alkali, drying and ashing the residue, and calculating the weight difference. Calcium is determined by precipitation and titration with potassium permanganate. Phosphorus is measured by forming a blue complex with molybdate and reading it spectrophotometrically.

Data Analysis

Descriptive Statistics and Distribution Analysis

Descriptive statistics were computed to summarize the physical and chemical parameters' central tendency, spread, and distributional properties. Mean, median, standard deviation and range were calculated, along with skewness and kurtosis, to assess the shape and symmetry of the distributions. Standard Error of the Mean (SEM) was used to quantify the precision of sample mean estimates (Agresti, 2018) and Huber's M-Estimator was applied to account for the influence of outliers (Wilcox, 2013). Statistical analysis was conducted using the R programming language (Field et al., 2012) and histograms were generated to visualize the distribution of key variables.

Key Parameters and Classification

Samples that did not meet SNI quality requirements were identified and compiled into Dataset-3 for further analysis. Principal Component Analysis (PCA) was applied to this dataset to identify key factors contributing to deviations from SNI standards. Physical parameters, including Mc, Dk, Mk, Bk and Fm, were standardized and analyzed using the 'prcomp' function in R (Everitt & Hothorn, 2011). Varimax rotation was employed to aid interpretation, and the suitability of the data for PCA was confirmed through Kaiser-Meyer-Olkin (KMO) and Bartlett's test (Hair et al., 2019). PCA condensed the original quality parameters into orthogonal components, simplifying the dataset while retaining maximal information. Regression scores derived from PCA outputs formed the basis for K-means clustering, which grouped samples into clusters based on similar characteristics. ANOVA was used to evaluate the significance of variables in distinguishing between clusters.

RESULTS

Descriptions and Distributions

Table 2 summarizes the descriptive statistics for the chemical quality of corn samples. The data reveal substantial variability in ash content and crude fat levels, while phosphorus content shows greater consistency. This variability, particularly in ash content and crude fat, underscores the need for stricter quality control to ensure consistent feed production. The standard error of the mean (SE Mean) across all parameters was low, indicating reliable sample means. Crude fat and phosphorus distributions were positively skewed, while other parameters showed more symmetrical distributions. Crude fat had a peaked distribution, whereas ash content and crude protein had flatter spreads, suggesting greater uniformity. The M-Estimator revealed that outliers, particularly in ash content, may have inflated the mean, highlighting the importance of robust statistical methods. These findings emphasize the variability in corn quality and the need for consistent monitoring to maintain feed production standards.

Table 2: Descriptive Statistics Results on Chemical Quality

Statistics	Chemical Quality					
	Ash	Crude Protein	Crude Fat	Crude Fiber	Calcium	P
Mean	5.21	10.91	3.91	3.09	0.83	0.35
SD	5.13	2.16	1.79	1.16	0.45	0.33
Min	0.54	7.21	0.90	0.81	0.10	0.01
Maximum	16.41	17.23	10.71	6.15	2.51	1.14
SE	0.66	0.28	0.23	0.15	0.06	0.04
Skewness[a]	0.94	0.37	1.51	0.37	0.77	1.09
Kurtosis[b]	-0.62	-0.47	3.28	-0.01	1.74	0.04
M-Estimator[c]	2.42	10.85	3.61	3.02	0.80	0.24

a: SE of skewness = 0.306; b: SE of Kurtosis = 0.604; c: Huber's M-Estimator, the weighting constant=1.339.

Table 3 presents the physical examination results of 1,781 corn samples received at the facility. The average moisture content (Mc) was 26.5%, with damaged kernels (Dk) at 1.02%, moldy kernels (Mk) at 1.78%, broken kernels (Bk) at 1.12%, and foreign maerial at 0.86%. Notably, the mean (SEM) standard error was higher for Mc (0.128) than for other parameters. The physical quality analysis revealed significant variability in moisture content (Mc), with values ranging from 11.21 to 39.5% and with an average of 26.5±5.42%. This inconsistency highlights variability in drying practices and environmental conditions affecting the corn. Damaged kernels (Dk) averaged 1.02%, moldy kernels (Mk) 1.78%, broken kernels (Bk) 1.12%, and foreign material (Fm) 0.86%, with all parameters showing minimal variation except for moisture content. Skewness and kurtosis analyses indicate that most parameters are moderately distributed, with occasional outliers, particularly in damaged and broken kernels.

Table 3: Descriptive Statistics Results on Physical Quality

Statistics	Quality Parameters				
	Moisture content	Damage kernel	Moldy kernel	Broken kernel	Foreign materials
Mean	26.50	1.02	1.78	1.12	0.86
SD	5.42	0.63	1.17	0.44	0.29
Min	11.21	0.09	0.09	0.18	0.09
Maximum	39.5	4.93	5.04	4.00	1.8
SE	0.128	0.014	0.027	0.01	0.006
Skewness[a]	-0.828	2.134	1.174	2.133	0.085
Kurtosis[b]	0.131	7.479	0.712	8.803	-0.092
M-Estimator[c]	27.43	0.911	1.529	1.063	0.861

a: SE of skewness = 0.058; b: SE of Kurtosis = 0.116; c: Huber's M-Estimator, the weighting constant=1.339.

The evaluation of corn quality, utilizing the initial physical parameters delineated above and benchmarked against the classification criteria stipulated in the SNI, highlights a notable disparity between the distribution of corn samples and the prescribed SNI benchmarks (Table 4). Specifically, the analysis reveals that 92.25% of the samples did not meet the established categorization criteria. A mere 5.95% are classified as Medium II, 1.29% as Medium I, and a mere 0.51% meet the stringent Premium classification criteria. These findings underscore the need for further scrutiny and potential corrective measures to enhance adherence to the designated quality standards.

Table 4: Sample Frequency and Percentage according to SNI Classes Category

SNI Category Class	N	%
Premium	9	0.51
Medium-I	23	1.29
Medium-II	106	5.95
Non -category (NC)	1643	92.25
Total	1781	100

Categorization under the Indonesian National Standard (SNI) requires compliance with multiple parameters. Among 1,643 non-categorical (NC) samples, 98.9% failed to meet the standard for moisture content (Mc), while 8.09% fell below the threshold for moldy kernels (Mk) (Table 5). In contrast, most samples met the criteria for damaged kernels (Dk), broken kernels (Bk), and foreign material (Fm), aligning with Premium or Medium I classes. These results indicate non-compliance is primarily driven by excessive moisture content and moldy kernels.

The 1625 non-categorical (NC) sample analysis provides insightful data on the moisture content distribution, a critical parameter for determining the quality of stored grain. Fig. 2 shows that the average moisture content for these samples stands at 27.66% with a standard deviation of 4.10%. This indicates a relatively high variability in moisture levels among the samples. The histogram (Fig. 3), a representation of Mc values sorted into percentile bins with a range of 1.2%, highlights the central tendency and spread of the data. Most samples have Mc above the average, concentrated within the normal range, typically from 20% to nearly 32%. However, the samples with Mc below the average are less frequent and appear more scattered across the lower moisture levels.

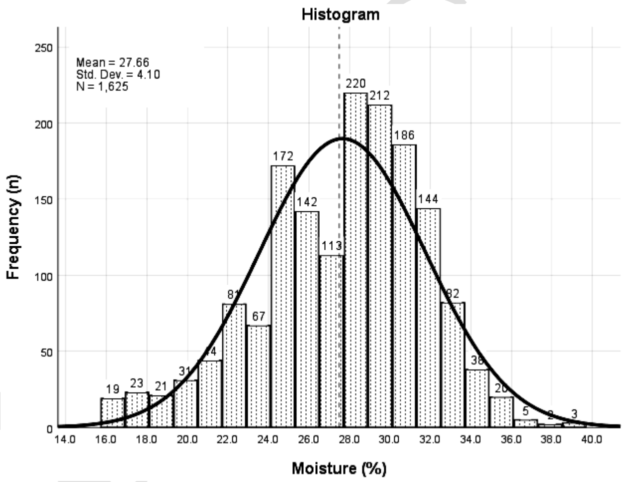

Fig. 3: Histogram of NC samples frequency in moisture content quality.

This distribution pattern reveals that although a substantial portion of the NC samples exhibit moisture levels above the desirable standard, a significant number also fall below, underscoring a widespread deviation from optimal moisture conditions. The prevailing high moisture content across these samples notably surpasses the thresholds recommended by the SNI standards, suggesting potential risks for grain quality, including increased susceptibility to molds and other storage issues. This insight necessitates further investigation into the factors contributing to such elevated moisture levels and the implementation of stringent quality control measures to align with industry standards.

Similar to the distribution observed in the Mc, the distribution of 133 NC samples in the Mk parameter is evident (Fig. 4). More than half of these samples tend to exhibit high levels (4.5-5%) of Mk. At the same time, the remaining are distributed in smaller proportions below the average. However, unlike the relatively normal distribution observed in the humidity parameter, the distribution of NC samples in the Mk appears to be less uniform. This indicates greater variability in the percentage of moldy seeds compared to the humidity parameter.

Principal Component Analysis

Table 6 shows that PC1 has an initial eigenvalue of 1.707, explaining 34.134% of the variance. This means that PC1 captures a substantial portion of the variability in the original dataset. PC2 has an initial eigenvalue of 1.306,

Table 5: Frequency and percentage distribution of non-categorical samples across distinct categories for each SNI parameter

Quality Class	Moisture content		Damage kernel		Moldy kernel		Broken kernel		Foreign materials	
	N	%	N	%	N	%	N	%	N	%
Premium	3	0.2	1619	98.5	529	32.2	823	50.1	1163	70.8
Medium I	0	0.0	24	1.5	525	32.0	820	49.9	480	29.2
Medium II	15	0.9		0.0	456	27.8		0.0		0.0
Non-Category (NC)	1625	98.9		0.0	133	8.1		0.0		0.0
Total	1643	100.0	1643	100.0	1643	100.0	1643	100.0	1643	100.0

Table 6: Total variance explained of initial and ratio to total of eigenvalue, Principal Component Analysis (PCA) on NC samples based on six SNI quality parameters

Principal Component (PC)	Initial Eigenvalues			Ratio to Total Sum of Eigenvalues (%)		
	Eigenvalue	Variance Explained (%)	Cumulative (%)	Total	Variance Explained (%)	Cumulative (%)
PC1	1.707	34.140	34.140	1.707	34.134	34.134
PC2	1.306	26.124	60.264	1.307	26.131	60.264

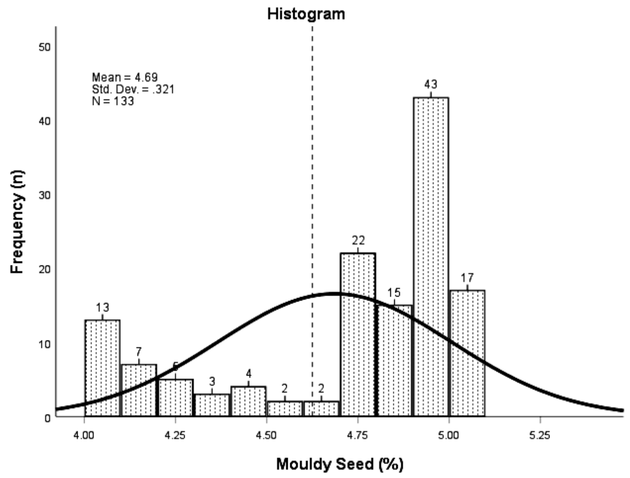

Fig. 4: Histogram of NC samples frequency for moldy kernel quality

explaining 26.131% of the variance, bringing the cumulative variance explained by PC1 and PC2 to 60.264%. The ratio of each eigenvalue to the total sum of eigenvalues indicates the proportion of variance each principal component accounts for. PC1's ratio of 1.707 suggests it significantly contributes to the overall variance captured by the principal components. Overall, PC1 captures the most significant amount of variance in the data (34.134%) and likely represents the most significant underlying structure or pattern in corn's physical qualities. This component is the primary factor driving variability among variables. PC2 captures additional variance (26.131%) but less than PC1, representing secondary patterns in the data.

Table 6 provides each variable's factor loadings and communalities in the PCA analysis to explore the relationships between variables and the principal components. These values offer insights into how each variable contributes to the principal components and what they signify in the context of the original dataset. Moldy kernels (Mk) had the highest commonality (0.766), with strong positive loading on PC1 (0.818), indicating moldiness as a key factor captured by this component. Damaged kernels (Dk) also showed high commonality (0.660) and were primarily represented by PC1 (0.813). Foreign material (Fm) and moisture content (Mc) both had commonalities of 0.637, with Fm influenced by both components and Mc primarily captured by PC2 (0.794). Broken kernels (Bk) had the lowest communality (0.512) and were moderately represented by PC2 (0.559). These results highlight the significant roles of Mk and Dk in determining deviations from SNI standards (Table 7).

Table 7: Factor loadings and communalities of six SNI quality parameters

Quality Parameter	Communalities	Principal Component (PC) Loading	
		PC1	PC2
Moldy kernel	0.766	0.818	-0.313
Damage kernel	0.660	0.813	0.007
Foreign material	0.637	0.610	0.515
Moisture content	0.637	-0.081	0.794
Broken kernel	0.512	0.001	0.559

Overall, PC1 captures the primary variance related to moldy kernels, damage, and foreign material, representing the main underlying structure of these quality parameters. PC2 captures additional variance related to moisture content and broken kernels, indicating secondary patterns in the data (Fig. 5). In our recent principal component analysis (PCA), two key statistical measures were utilized to assess the data's suitability for PCA: the Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity. Despite a KMO value of 0.513, which typically suggests a lower suitability for PCA due to insufficient common factors among variables, the communalities for all variables were found to exceed 0.6.

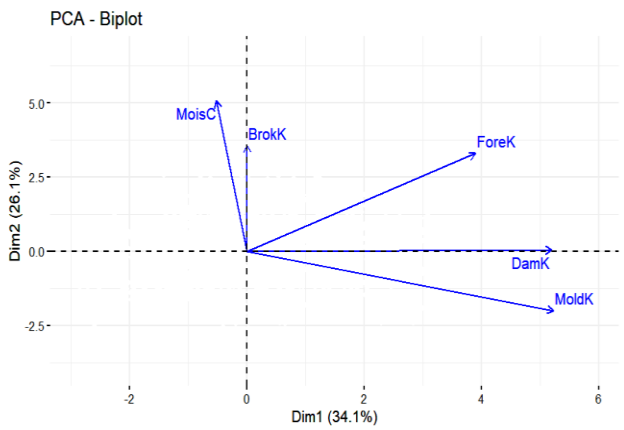

Fig. 5: PCA bibplot for combination of factor loading PC1 (Dim1) and factor loading PC2 (Dim2).

This indicates that a significant portion of each variable's variance is being successfully captured by the principal components, affirming the relevance and effectiveness of the PCA in this context. Moreover, Bartlett's Test resulted in a p-value of 0.000, confirming the presence of substantial correlations among the variables and further justifying the use of PCA. These findings suggest that the PCA captures meaningful underlying patterns, providing a robust basis for dimensionality reduction and further analysis. This successful extraction of principal components, evidenced by high communalities, supports using PCA to simplify the data structure without significant loss of information, contrary to initial indications from the KMO value.

Classification

The PCA identified Mk and Mc as two factors representing common symptoms across all physical parameters observed in NC samples. The regression scores obtained from the PCA analysis formed the basis for the K-means classification into two clusters. Out of 1,625 samples, 782 (48.12%) were classified into Cluster I, which includes samples with higher moisture content (Mc) and lower mold levels (Mk). This indicates that the corn in this cluster is wetter but generally less affected by mold. Meanwhile, 843 samples (51.88%) were assigned to Cluster II, characterized by lower moisture content (Mc) and higher mold levels (Mk), suggesting that while this corn is drier, it is more prone to mold contamination. Fig. 6 shows that the values of Mc, Fm, and Bk are higher in Cluster I, whereas Mk and Dk are higher in Cluster II. A detailed examination of Fig. 6 reveals that only the parameters Mk and Mc have non-overlapping standard deviations. Specifically, Mk is 1.17±0.63 in Cluster I and 2.30±0.27 in Cluster II, while Mc is 30.32±1.72 in Cluster I and 25.19±2.59 in Cluster II. These results suggest that the parameters Mk and Mc can reliably represent the physical quality condition of corn kernels. Based on the description above, Cluster I is characterized by corn kernels with high values for Mc, Fm, and Bk and low values for Mk and Dk. Cluster II consists of corn kernels with high Mk and Dk values and low Mc, Fm, and Bk values.

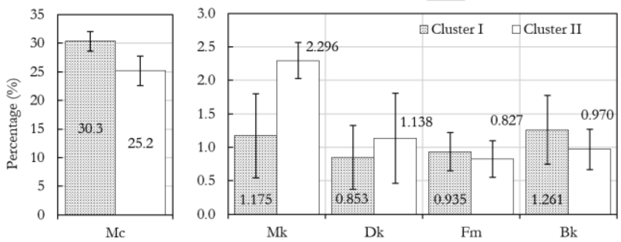

Fig. 6: Moisture content and physical parameters of corn kernels based on clustering.

DISCUSSION

The quality of corn entering the feed mill shows an average Mc of 26.50±5.42%, with a range between 11.21 to 39.50%. This finding is similar to the moisture content value reported by Fajar et al. (2021) but significantly higher than those found by Coşkun et al. (2006), Mukkun et al. (2018) and Zambiasi et al. (2020). Generally, the moisture content is below SNI standards, whereas the quality measures for Dk, Mk, Bk, and Fm are better than SNI standards. Separate assessments, except for moisture content, indicate that these parameters meet SNI standards. The trend of relatively low variability in quality (Table 3) is observed in most physical quality parameters, except for Mc, which shows considerable variability. Dk averages 1.02±0.63%, consistently within the premium class (Dk≤3%); Mk average 1.78±1.17%, fluctuating between Premium class (Mk≤1%) and Medium I class (Mk≤2%); Bk average 1.12±0.44%, typically falling within the Medium I class (Bk≤5%); and Fm averages 0.86±0.29%, tending towards the premium class (Fm≤1%). The levels of broken kernels, moldy kernels, and foreign material found in this study were higher than those reported for U.S. corn. The 2023/2024 Corn Harvest Quality Report shows average values of 0.4% broken corn, 0.1% foreign material, and 0.9% total damage across 611 samples from major U.S. production regions, indicating consistently high physical quality (U.S. Grains Council, 2023).

Simultaneous assessment and evaluation of all parameters against SNI standards revealed that 92.25% of corn samples were below SNI quality standards, meaning only 7.75% met the category, with less than 1% qualifying as Premium (Table 4). A high proportion of NC corn aligns with previous studies by Fajar et al. (2021), who reported that over 97% of corn received at feed mills was below SNI standards. Table 5 shows that the parameters for Dk and Fm tend to fall within the premium class; Bk is relatively distributed between the Premiums and Medium I, while the Mc and Mk parameters are distributed across all three class levels. Further analysis of the sample distribution patterns in the Mc and Mk parameters reveals distinct trends. Fig. 3 illustrates that samples with medium Mc values (28%≤Mc≤32%) are prevalent, with a smaller portion exhibiting low Mc values (16%≤Mc≤28%) and a tiny fraction showing high Mc values (32%≤Mc≤40%). In contrast, Fig. 4 shows that the Mk parameter exhibits two primary distribution clusters: above average (Mk≥4.69) and below average (Mk≤4.69), both indicating Mk quality below SNI standards.

The key parameters hypothesized to describe NC corn quality conditions comprehensively are derived from the results of the PCA analysis (Table 7). PC1 primarily represents variables related to Mk, Dk, and Fm. The high loadings on these variables indicate that PC1 captures significant aspects of corn quality and general contamination. PC2 is primarily associated with Mc, followed by Bk. These components likely represent physical quality and feed integrity factors, encompassing overall quality, consistency, and feed safety. While Mk and Mc parameters provide useful summaries, relying solely on these can overlook nuanced interactions between other variables. For instance, the moderate loadings of Fm in both PC1 and PC2 suggest that it has a broader impact, indicating that additional monitoring may be necessary.

Simplifying variables using K-Mean Clustering based on PCA outputs resulted in two clusters. In line with the PCA results, Mk and Mc showed relatively low variability within each cluster (based on error bars). In contrast, other parameters (Dk, Fm, and Bk) exhibited more diverse value distributions, overlapping between clusters (Fig. 6). This clustering outcome demonstrates good consistency with practical applications, as it was also found that most corn kernel parameters met the SNI standards, except for moisture content and moldy kernels. It should be noted that the moisture content and moldy kernels in this study are two variables that distinguish between the two clusters. Mk is high, and Mc is low in Cluster 1, and conversely, Mc is high, and Mk is low in Cluster II. This does not imply a negative correlation between Mk and Mc. Damage to corn kernels increases the risk of mold growth and insect infestation during storage. Broken kernels create openings that disrupt airflow and form moisture pockets, accelerating quality degradation. Preventing such damage is essential to maintain corn quality for feed use (GuiXiang et al., 2023).

Mk is a possible indication of mycotoxins produced by fungi (Munkvold et al., 2019) and the command contaminants of moldy feeds (Zhu et al., 2023). Molds remain a prevalent problem in developing countries due to insufficient attention to food safety aspects within the grain market chain. An earlier study on corn mycotoxin evaluation in feed mills by Tangendjaja et al. (2008) found that the mycotoxin concentration was significantly higher in Indonesian corn samples compared to those from the USA and Argentina. Mycotoxin can develop during the production, harvesting, or storage of grains, nuts, tubers, and other crops (Wu, 2007). High Mc in corn creates an environment conducive to the growth of molds and fungi, which can further contaminate the corn with mycotoxins, such as aflatoxin. Mold growth not only affects the quality of the corn but can also increase the level of foreign material as the molds proliferate and produce spores. The relationship between moisture content and mold growth is well-documented (Sinha & Bhatnagar, 2000). Magan et al. (2003) explore how high moisture content promotes mold growth, leading to significant quality degradation in stored grains, as well as Rodrigues et al. (2014) revealed that some physical problems (fermented, moldy, and soft grains) generally increased as moisture increased. Kassa et al. (2025) stated that corn kernels that were threshed at 17% moisture content showed lower mold growth than those that were at 23%.

Shifting to the contamination from foreign materials in corn. The PCA results reveal that the variable Fm is positioned at a transitional juncture between Cluster I and Cluster II. The difference in Fm between the two clusters is a mere 0.11%, with overlapping deviations, indicating no substantial difference even though the average Fm is slightly higher in Cluster I. High levels of foreign material in corn batches can indicate poor handling and storage practices. Such practices often coincide with inadequate moisture control, leading to increased spoilage and quality degradation. Foreign materials, such as dust, soil, or plant debris, can retain moisture and increase the overall moisture content of the corn batch, creating localized areas of high humidity that further promote mold growth. It provided comprehensive insights into the handling and storage of grains, emphasizing the role of foreign materials as indicators of poor post-harvest practices (Chakraverty et al., 2003). A review by Payne et al. (2023) describes how foreign material affects overall grain quality, including moisture retention and contamination risks.

These findings underscore the significant variability in corn chemical quality, which is crucial for feed production. The observed high variability in ash and crude fiber suggests that corn quality can differ widely, impacting feed consistency and effectiveness. The skewness values reveal that distributions for crude fiber and phosphorus are positively skewed, indicating that higher values are more frequent. This suggests that, on average, these components have higher levels in the corn samples. In contrast, the other parameters exhibit more symmetrical distributions. Kurtosis values further describe the distribution shapes, with crude fiber showing a high kurtosis (3.28), indicating a more peaked distribution around the mean. Conversely, the ash and crude protein distributions are flatter, suggesting a more uniform spread of values. As in the physical evaluation, the diversity in chemical content is undoubtedly influenced by the varying origins of the corn kernels (Vargas et al., 2023), which differences in farming practices (Schulz et al., 2020), post-harvest handling, and environmental factors across regions contribute to this inconsistency (Ali et al., 2021). Carbas et al. (2024) emphasized that corn's chemical and physical quality is greatly influenced by environmental factors (climate, planting location), which causes variability in its nutritional quality. These findings support the need to monitor the quality of raw corn materials in poultry feed production and the importance of selecting the right variety and planting location.

The substantial variability in the chemical quality of corn kernel highlights the need for enhanced quality control procedures in feed production. Accurate and consistent measurement of these parameters is crucial for optimizing feed formulations and ensuring the health and productivity of livestock. Future research should explore the causes of variability in corn quality, including factors such as growing conditions, harvest methods, and storage practices. Additionally, further studies could investigate the development of advanced quality control techniques, such as real-time monitoring and predictive analytics, to address the issues identified in this study. Evaluating the impact of these factors on animal performance and feed efficiency would provide valuable insights for improving feed quality and consistency.

Conclusion

This study highlights significant challenges in maintaining consistent corn quality for feed production, particularly due to high moisture content (Mc) and variability in chemical parameters like crude fat and ash. While most physical parameters, such as damaged kernels (Dk), broken kernels (Bk), and foreign materials (Fm), conform to SNI standards, excessive moisture content fosters mold growth and mycotoxin risks, posing a primary quality concern.

Principal Component Analysis (PCA) identified Mc and moldy kernels (Mk) as key factors differentiating non-compliant samples, underscoring the need for targeted interventions. To improve feed safety and quality, stakeholders must prioritize enhanced monitoring, stricter adherence to SNI standards, and improved post-harvest handling practices. Future research should explore advanced drying technologies, effective storage methods, and real-time quality monitoring systems to mitigate moisture and mold-related issues in corn supply chains.

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