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Visible and infrared spectroscopy (VIS-NIRS) to predict the mineral composition of beef

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Abstract

Visible and near-infrared spectroscopy (VIS-NIRS) was evaluated for its ability to predict macro- and micromineral concentrations in beef. Samples from the *Longissimus thoracis* muscle were used to collect spectra in the range between 200 and 2500 nm. Partial least squares regression (PLSR) models were developed for macrominerals (Ca, K, Mg, P, and S) and microminerals (Co, Cr, Cu, Fe, Mn, Se, and Zn). The coefficients of determination (R^2) of the calibration models for macrominerals ranged from 0.60 to 0.99, with the highest values in the prediction stage observed for P (R^2 = 0.66) and S (R^2 = 0.53). For microminerals, the R^2 values of the calibration models ranged from 0.31 to 0.99; however, for predictive performance, the R^2 values were extremely low, Zn R^2 < 0.01 and the others NA (not applicable). Overall, VIS-NIRS demonstrated potential for quantifying minerals associated with organic molecules in beef. However, further studies are needed to increase the robustness and predictive accuracy of the models applied to the quantification of macro- and microminerals in fresh beef samples.

1. Introduction

Beef is an important source of high-quality protein, as well as essential vitamins and minerals, playing a significant role in human nutrition and metabolic health (Nuernberg, 2009). In response to the growing demand for rapid, sustainable, and non-destructive analytical methods to assess meat quality and nutritional value of meat, visible and near-infrared spectroscopy (VIS-NIRS) has emerged as a promising analytical tool (Bonin et al., 2020). VIS-NIRS technology is based on the interaction between electromagnetic radiation and the chemical constituents of matter, generating spectral information that can be considered a molecular fingerprint of the analyzed samples (Segtnan et al., 2009; Prieto et al., 2017). In the spectral range between 350 and 2500 nm, VIS-NIRS provides information related to the chemical composition and physical properties of meat, including intramuscular fat content, collagen, and fatty acid composition (Gobrecht et al., 2016; Bonin et al., 2020; Guo and Jayan, 2023).

In the meat industry, VIS-NIRS has been applied to differentiate between fresh and frozen-thawed meat, predict sensory acceptance, detect adulteration, and authenticate products, highlighting its potential for integration into industrial quality control systems (Reis, 2017; Barragán-Hernández et al., 2020; Weng et al., 2020). In a recent study, Pereira et al. (2025) evaluated the use of VIS-NIRS as a tool for sex identification in refrigerated bovine carcasses, achieving 75.5% accuracy, indicating its potential for carcass classification and distinction of meat from animals of different sexes, a relevant aspect for the industry.

Despite the proven performance of VIS-NIRS in predicting the main nutritional components, its application in determining minerals in meat remains limited, with most studies focusing on other matrices, such as fruits, vegetables, and soils (Patel et al., 2020; Fatchurrahman et al., 2021; Fodor et al., 2024). The accuracy of predictive models is influenced by several factors, including sample moisture content, particle size, temperature, spectral preprocessing techniques, and the quality and representativeness of calibration datasets (Savoia et al., 2020; Patel et al., 2021).

In this context, the development of robust calibration models, most commonly based on partial least squares regression (PLSR), for mineral composition of beef is essential for consolidating the VIS-NIRS technique (Pereira et al., 2025) and contribute to the development of rapid and non-destructive approaches for the nutritional characterization of beef and supporting the future implementation of this technology in scientific research and industrial meat practices.

Given the importance of beef as a bioavailable source of essential minerals, and considering that diet, genetics, and environment influence the deposition of these elements in skeletal muscle, it becomes fundamental to understand how biological variability impacts its composition (Falowo, 2021; Meng et al., 2024). Nutritional strategies, such as adjustments in cation-anion balance and mineral supplementation, can modify tissue absorption and retention, affecting the nutritional value of beef (Meng et al., 2024) and consequently human health (Nuernberg, 2009). In view of the

nutritional relevance that the minerals present in beef represent for human health and the need to trace their quality throughout the production chain, the use of effective analytical methods to monitor the mineral composition of meat becomes essential, especially in a context of growing concern about nutritional deficiencies and public health (Agarwal and Fulgoni, 2024).

In this context, VIS-NIRS spectroscopy emerges as a promising fast and non-destructive tool; however, its predictive capacity for minerals depends on the amplitude of compositional variability and the robustness of chemometric models, since these elements do not exhibit direct absorption in the near-infrared (Patel et al., 2020). Therefore, the objective of the present study was to evaluate the feasibility of VIS-NIRS combined with chemometric modeling to predict macro- and micromineral concentrations in bovine *longissimus* muscle.

2. Material and methods

2.1 Animals and sample preparation

Forty-four beef samples were analyzed, including 25 samples from F1 Angus × Nelore heifers and 19 from entire Nelore bulls, all finished in feedlots in Terenos, Mato Grosso do Sul, Brazil. They were fed isoproteical and isoenergetic diets, meeting maintenance and growth requirements according to BR-Corte (2016).

The animals were slaughtered in a commercial slaughterhouse and after 24 hours of cooling, the carcasses were ribbed between the 5th and 6th ribs for the collection of 10 cm tick *longissimus thoracis* (LT) samples collected from the fifth rib of the carcasses in a. The samples left the slaughterhouse vacuum-packed and transported in thermal boxes packed with ice to the processing site, the Meat Technology and Processing Laboratory – Qualicarnes at the Faculty of Veterinary Medicine and Animal Science of the Federal University of Mato Grosso do Sul - FAMEZ/UFMS, where connective tissue and subcutaneous and intermuscular fat were removed, leaving only the muscle tissue of the sample. Knives and workbenches were sanitized between the handling of each sample to avoid contamination.

The meat was cut into slices 2.54 cm thick, identified, and vacuum-packed, then immediately transported in insulated boxes with ice to the processing site for spectral sampling. For the mineral analysis, steaks 2.54 cm thick were used, identified and vacuum-packed, immediately frozen in a horizontal freezer maintained at -20°C until grinding in a KD Eletro industrial blender. They were ground until particles of 4 to 8 mm were obtained, placed in 50 mL plastic Falcon tubes, capped with parafilm, frozen in liquid nitrogen, and subjected to lyophilization in a lyophilizer JJ Científica LJJ02 at -40°C and 500 mmHg pressure for 5 days until fully lyophilized samples were obtained.

2.2 VIS–NIRS spectral acquisition

The spectra were collected at Embrapa's Animal Nutrition and Greenhouse Gases Laboratory using a NIRFlex Solids spectrometer (BUCHI Labortechnik AG, Switzerland). The samples were ground in a KD Eletro industrial blender until they reached particle sizes of 4 to 8 mm, immediately prior the scans and distributed evenly on Petri glass dishes, and scanned in the range of 200 to 2500 nm, with 32 scans per sample. The average spectra were calculated using Buchi Operator software and exported for chemometric analysis in The Unscrambler X v 10.1 software.

2.3 Mineral analysis

Mineral determinations were performed at the Mineral Metabolism Laboratory (FAMED/UFMS). For this purpose, the samples were ground and freeze-dried, and 0.250 grams of sample was weighed for subsequent digestion, where 1 mL of ultrapure water (18.2 milli Q) plus 1 mL of hydrogen peroxide (H_2O_2) (30%, Merck) and 3 mL of nitric acid (65%, Merck, Darmstadt, Germany) were added. The samples were digested in a digestion block (TE-041/25, TECNAL, São Paulo, Brazil). The time and temperature program for digestion was in accordance with Table 1.

Table 1
Time and temperature program for digestion in the block

Temperature (°C)	Time (min)	Ramp (min)
100	60	15
120	90	15
150	30	15

The concentrations of calcium (Ca), potassium (K), magnesium (Mg), phosphorus (P), sulfur (S), cobalt (Co), chromium (Cr), copper (Cu), iron (Fe), manganese (Mn), selenium (Se), and zinc (Zn) were quantified by inductively coupled plasma optical emission spectrometry (ICP-OES; iCAP 6300 Series, Thermo Scientific, UK).The operating conditions of the ICP-OES for analysis were as follows: radiofrequency power of 1150 W, pump flow of 50 rpm, plasma argon flow of 12 L/min, auxiliary argon flow of 0.50 L/min, nebulizer gas flow of 0.50 L/min, and axially visualized observation mode.

A standard multi-element solution containing 1000 mg/L of each element for the ICP-OES test was prepared by dilution (SpecSol, Quinlab, Jacareí, SP, Brazil). Eight different concentrations were used to construct calibration curves for quantitative mineral analysis, with a concentration range for the elements of 0.005; 0.01; 0.025; 0.05; 0.1; 0.25; 0.5, and 1 mg/L.

The detection limit of the method was determined as 3× SD of the blank/slope (curve slope), where SD is the standard deviation value as the analyte concentration approaches 0, and B is the blank signal. The limit of quantification (LOQ) was defined as 10 × SD of the blank/slope (curve slope). Table 2 contains the wavelengths, detection limits (LOD), quantification limits (LOQ), and correlation coefficient (R^2) for each element quantified in this study.

Table 2
Operating conditions used in ICP-OES analysis: wavelengths, limits of detection (LOD), quantification (LOQ) and correlation coefficient (R^2) in the emission signal measurements for minerals in beef.

Elements	Wavelengths (nm)	Limit of detection LOD (mg/L)	Limit of quantification LOQ (mg/L)	Correlation coefficient (R2)
Ca	393.366	0.0667	0.2222	0.9979
Co	228.616	0.0011	0.0036	0.9924
Cr	283.563	0.0064	0.0213	0.9943
Cu	324.754	0.0112	0.0372	0.9914
Fe	259.940	0.0116	0.0385	0.9993
K	766.490	0.4195	1.3982	0.9997
Mg	279.553	0.0042	0.0140	0.9920
Mn	257.610	0.0011	0.0037	0.9925
P	177.495	0.4707	1.5690	0.9968
S	180.731	0.0306	0.1021	0.9954
Se	196.090	0.0082	0.0273	0.9928
Zn	213.856	0.0015	0.0050	0.9927

2.4 Chemometric analysis

Spectral data were analyzed using partial least squares regression (PLSR) implemented in The Unscrambler X v.10.1software (CAMO Software AS, Oslo, Norway). Principal component analysis (PCA) was initially applied to the raw spectra to identify potential spectral outliers and evaluate the distribution of samples prior to model development (Barlocco et al., 2006; Martens and Martens, 2000).

The datasets were randomly divided into calibration (60%) and prediction (40%) sets. Calibration models were evaluated using internal cross-validation, with performance assessed by the cross-validation coefficient of determination (R^2_cv) and the cross-validation root mean square error (RMSE_cv). Prediction performance was evaluated using independent test samples, expressed as the coefficient of determination for prediction (R^2_p) and the root mean square error of prediction (RMSE_p).

The robustness of the model was additionally evaluated using the residual predictive deviation (RPD), calculated as the ratio between the standard deviation of the reference data and the prediction error (Williams, 1987). The models were classified as excellent (RPD > 2.0), acceptable (1.4 < RPD < 2.0), or unreliable (RPD < 1.4), following Minasny and McBratney (2013).

Spectral preprocessing methods were applied to minimize the effects of dispersion and emphasize chemical information (Geesink et al., 2003). The methods evaluated included no preprocessing, baseline correction, standard normal variable (SNV), multiplicative scatter correction (MSC), extended multiplicative scatter correction (EMSC), first derivative, and second derivative. The optimal preprocessing method for each mineral was selected based on the highest R^2 and lowest prediction error. The contribution of each preprocessing method to the PLSR models is shown in Table 4.

Table 4
Calibration, internal validation, and prediction curves obtained from VIS-NIRS spectra for predicting and quantifying calcium (Ca), potassium (K), phosphorus (P), magnesium (Mg), sulfur (S), copper (Cu), iron (Fe), manganese (Mn), and zinc (Zn) in fresh beef.

			Calibration			Internal validation			Prediction		
Mineral	**F**	**Spectral pre-processing**	**R²c**	**RMSEc**	**RPDc**	**R²cv**	**RMSEcv**	**RPDcv**	**R²p**	**RMSEp**	**RPDp**
Ca	2	2nd Derivative	0.95	0.74	4.84	0.30	3.03	1.18	NA	4.40	0.81
K	7	BAS	0.60	441.33	1.99	0.13	677.42	1.29	NA	1091.29	0.80
P	5	1st Derivative	0.99	504.17	13.53	0.74	3596.68	1.90	0.66	4051.79	1.68
Mg	7	MSC	0.68	3.00	2.29	0.52	3.64	1.89	NA	12.76	0.54
S	5	1st Derivative	0.99	14.26	14.34	0.65	117.72	1.74	0.53	151.23	1.35
Cu	4	SNV	0.31	0.02	1.39	0.23	0.02	1.35	NA	0.03	0.94
Fe	5	1st Derivative	0.99	0.05	17.07	0.99	0.05	17.07	NA	0.92	0.85
Mn	5	2nd Derivative	0.99	0.00	215.50	0.08	0.04	1.10	NA	0.05	0.83
Zn	1	2nd Derivative	0.73	0.57	2.16	0.17	1.03	1.24	0.0006	1.41	0.90

F: The ideal number of factors used in the PLSR model; Spectral pre-processing: Spectral pre-processing methods to reduce the influence of sample presentation; BAS: Baseline correction, MSC: Multiplicative dispersion correction, SNV: Standard normal variation; 1st Der: First derivative; 2nd Der: Second derivative; NA: Not Applicable; R²c: Coefficient of determination of calibration; R²cv: Coefficient of determination of cross-validation; R²p: Coefficient of determination of prediction; RMSEc: Standard error of calibration; RMSEcv: Standard error of cross-validation; RMSEp: Standard error of prediction; RPDc: Residual standard deviation of calibration; RPDcv: Residual standard deviation of cross-validation; RPDp: Residual standard deviation of prediction.

3. Results

3.1 Descriptive statistics of mineral composition of samples

The descriptive statistics of mineral concentrations in beef samples used for VIS-NIRS model development are presented in Table 3. A wide variability among the evaluated minerals was observed, reflecting physiological, metabolic, and nutritional composition of beef samples.

Table 3
Descriptive statistics for mineral concentration (mg/100g) in VIS-NIRS datasets used to predict the quality of fresh beef.

Mineral	Average	Máx	Mín	Range	SD	Skewness
Ca	11.66	20.68	0.59	20.08	3.56	-0.17
K	7654.84	9242.95	4820.96	4421.99	876.75	-0.65
P	11588.55	24462.99	1266.72	23196.27	6821.03	0.14
Mg	68.36	82.66	42.22	40.44	6.90	-1.00
S	1024.50	1392.62	622.21	770.41	204.53	-0.23
Cu	0.11	0.17	0.07	0.10	0.03	0.43
Fe	4.24	5.72	2.32	3.40	0.78	-0.27
Mn	0.06	0.15	0.05	0.14	0.04	0.74
Zn	9.96	12.28	7.42	4.86	1.27	0.12

Average: average concentration of each mineral per 100g of fresh beef; Max: maximum concentration; Min: minimum concentration; Range: Difference between the maximum and minimum values; SD: standard deviation; Skewness: Negative values indicate left skewness (higher concentration of samples below the average), values close to zero indicate normal distribution.

The K and P had the highest average concentrations, reaching 7654.8 and 11,588.6 mg/100 g, respectively, confirming their role as predominant macrominerals in skeletal muscle. These elements are essential for osmotic balance and energy metabolism, as previously described by FAO (2002) and Afonso et al. (2019). Mg and S showed lower dispersion, with standard deviations of 6.89 and 204.5 mg/100 g, respectively, indicating a more homogeneous distribution among the samples.

The asymmetry values were close to zero for most minerals, suggesting an approximately normal data distribution, except for Mg, which showed negative asymmetry (-1.00), indicating a higher frequency of samples with above-average values. The mean Mg concentration was 68.36 mg/100 g, exceeding the values reported by Bender (1992) and USDA (2018). The S had a relatively high mean concentration (1024.5 mg/100 g), which can be attributed to its incorporation into sulfur-containing amino acids, such as cysteine and methionine, which are abundant in muscle proteins.

The Ca had an average concentration of 11.66 mg/100 g, which is consistent with international reference data (Bender, 1992; USDA, 2018), although the wide variation (20.08 mg/100 g) and standard deviation (3.56 mg/100 g) indicate considerable heterogeneity among the samples. These results highlight the influence of diet, genetics, and environmental factors on mineral deposition in skeletal muscle (Falowo, 2021; Meng et al., 2024).

Among the microminerals, Cu had an average concentration of 0.113 mg/100 g, similar to the values reported by Bender (1992), while Fe had an average concentration of 4.237 mg/100 g, exceeding the values reported by Bender (1992) and USDA (2018). The distribution of Fe was approximately symmetrical, which is desirable for predictive modeling. Mn had a low average concentration (0.0587 mg/100 g) and high positive asymmetry, indicating concentrations close to the lower limit positive. Zn had the highest average concentration among the microminerals (9.96 mg/100 g) and a relatively balanced distribution, which favors the performance of the VIS-NIRS model.

The concentrations of Co, Cr, and Se were below the analytical detection limit, impossibiliting the quantitative evaluation. This result is consistent with Bender (1992), who does not report values for these elements in beef, and with the USDA (2018), which reports only Se at trace levels.

3.2 VIS-NIRS calibration, validation, and prediction models

The statistics of the regression models developed from the VIS-NIRS spectra for mineral prediction are presented in Table 4. Considering only the best performing models, the coefficients of determination for calibration (R^2c) ranged from 0.60 to 0.99. For cross-validation, the R^2cv values ranged from 0.13 to 0.99, while the external prediction coefficients (R^2p) were low to moderate, ranging from not applicable (NA) to 0.66.

The P and S showed the best overall performance, while Ca, K, and Mg showed intermediate performance. For the microminerals Cu, Fe, Mn, and Zn, the models showed limited or inadequate predictive ability.

4. Discussion

The mineral composition of beef reflects the complex interactions between feed intake, ruminal metabolism, absorption efficiency, homeostatic regulation, and tissue deposition in ruminants. Macrominerals such as K and P had the highest concentrations, which is consistent with their central roles in muscle physiology. K is easily absorbed and widely retained in intracellular compartments, contributing to stable muscle concentrations, while P benefits from efficient intestinal absorption and extensive salivary recycling in ruminants, resulting in sustained systemic availability (FAO, 2002; Afonso et al., 2019; Tizioto et al., 2015).

From a human nutrition perspective, the high concentrations of K and P in beef reinforce its relevance as a source of essential minerals. K plays a fundamental role in regulating blood pressure, acid-base balance, and neuromuscular function; its adequate intake is associated with a reduced risk of hypertension (WHO, 2012). Phosphorus (P) is a central component of energy metabolism, bone structure, and cellular integrity, and is widely recognized as an essential nutrient in the composition of foods of animal origin (USDA, 2023). Therefore, the consistent presence of these macrominerals in beef contributes significantly to the nutritional quality of the human diet.

From a spectroscopic point of view, the relatively better predictability observed by VIS-NIRS for P, compared to other minerals, can be attributed to its indirect association with organic constituents of muscle, such as phospholipids, nucleotides, and phosphorylated metabolites formed during *post mortem* glycolysis. These compounds exhibit detectable absorption characteristics in the VIS-NIRS region, allowing for more robust chemometric modeling, as also reported by Patel et al. (2020).

The macrominerals Mg and S showed more homogeneous distributions, reflecting stricter metabolic control. The Mg absorption occurs mainly in the rumen and is influenced by ruminal pH and K intake, but homeostatic mechanisms limit large fluctuations in soft tissues (Spears, 2024). The S is widely incorporated into S-containing amino acids synthesized by ruminal microorganisms, particularly cysteine and methionine, and subsequently deposited in muscle proteins. This biochemical linkage explains both the relatively high S content and its moderate predictability in the VIS-NIRS region, which is likely driven by spectral signals associated with protein structure rather than the mineral itself (Patel et al., 2020).

From a human nutrition perspective, these findings reinforce the nutritional importance of both elements. The Mg is essential for enzymatic reactions, neuromuscular function, glucose metabolism, and blood pressure control; adequate intake is associated with a reduced risk of cardiovascular and metabolic disorders (WHO, 2012). The S although not usually treated as an isolated nutrient in dietary recommendations, has nutritional relevance as a component of sulfur-containing amino acids, such as methionine and cysteine, which are essential for protein synthesis, glutathione formation, and maintenance of the structural and functional integrity of tissues (WHO, 2007; FAO, 2013). Thus, the relatively stable position of Mg in muscle and the incorporation of S into the protein fraction reflect regulatory

mechanisms of mineral metabolism in ruminants and benefits for the nutritional quality of meat in human food (Patel et al., 2020; Spears, 2024).

The Ca concentrations are low and variable, in line with its strict endocrine regulation and preferential storage in bone tissue rather than muscle tissue (Herdt and Hoff, 2011). From a human nutrition perspective Ca is essential for bone mineralization, muscle contraction, nerve transmission, and blood clotting, and adequate intake is crucial for preventing disorders such as osteopenia and osteoporosis (WHO, 2004; FAO, 2011). Although beef is not considered a primary source of Ca, its contribution, albeit modest, is part of the total dietary intake, especially in dietary patterns with reduced dairy consumption (FAO, 2011; USDA, 2023). Consequently, Ca showed limited predictability by VIS-NIRS, as its low electronegativity and minimal association with organic compounds active in VIS-NIRS restrict spectral sensitivity (Schmitt et al., 2014). Similar limitations have been reported for K, whose ionic nature and strong hydration in fresh meat reduce its spectral detectability (Patel et al., 2020), both indicate low predictive capacity and suggest overfitting, i.e., it predicts calibration samples well but fails to adequately predict external samples, capturing not only real patterns but also noise or random variations in the training set. This can be reduced with greater variability and a larger number of samples.

The bioavailability of macrominerals is influenced by several factors, such as the age of the animal, the chemical form of the minerals, interactions with other nutrients, and the composition of the diet (Moraes and Costa, 2023). In muscle tissue, macrominerals perform fundamental functions; Ca and Mg, for example, are cofactors in muscle contraction, while K, Na and Cl participate in maintaining membrane potential and osmotic balance (Sales et al., 2011; Costa e Silva et al., 2015). The metabolism of these elements is regulated by hormonal and metabolic mechanisms that control their absorption, tissue distribution, and excretion (Hocquette, 2010).

The metabolism of macrominerals in muscle directly affects the quality of beef. The mineral composition of muscle tissue influences technological and sensory attributes, such as water retention capacity, tenderness, pH, and flavor (Tizioto et al., 2015; Oh et al., 2017; Honig et al., 2022). The concentration of calcium, for example, regulates the activity of proteolytic enzymes, such as calpain, responsible for the degradation of myofibrillar proteins in the post-mortem period, which contributes to meat tenderization (Lundberg et al., 1987).

The texture and tenderness of meat are also modulated by mineral-dependent enzymes, as observed in studies with peroxiredoxin 6 (Prdx6), which demonstrated its involvement in the tenderizing process during the first hours after slaughter (Wang et al., 2023). The pH of meat, influenced by the electrolyte balance of sodium and potassium ions, significantly affects water retention capacity and, consequently, the juiciness and appearance of the final product (Satter and Roche, 2011; Higuero et al., 2020). In addition, the flavor of meat can be indirectly affected by the metabolism of macrominerals, since these nutrients participate in biochemical reactions during the maturation process, which result in the formation of volatile aromatic compounds (Satter and Roche, 2011).

Minerals such as Cu, Mn, and Zn showed low concentrations and high variability, reflecting strong ruminal antagonisms and limited absorption efficiency. The bioavailability of Cu is significantly reduced by interactions with S and Fe, Mn absorption is inherently low, and Zn competes with other divalent cations during intestinal absorption (Spears et al., 2022). These physiological constraints explain both the variability observed in muscle concentrations and the low predictive performance of VIS-NIRS for these elements. From the perspective of human nutrition, Cu, Mn, and Zn are considered indispensable trace elements. Zn, in particular, stands out for its role in immune competence and cell development, while Cu contributes to iron metabolism and protection against oxidative stress; Mn, in turn, integrates antioxidant and metabolic enzymatic systems (FAO, 2001; WHO, 2004). Beef is a source of highly bioavailable Zn and Cu, especially when compared to plant sources that contain phytates and other inhibitors of mineral absorption. Thus, even when present in low concentrations, these microminerals are significantly important for the nutritional density of

the human diet, reinforcing the importance of mineral balance in ruminant feeding to ensure adequate nutritional quality for the end consumer (USDA, 2023).

The Fe represented a particular case, as the excellent calibration statistics contrast with the low external prediction, indicating overfitting, i.e., the model fits the calibration data very well, but captures not only the real patterns, but also the noise or random variations of the training set, therefore not maintaining performance when tested with new samples. Although Fe is abundant in heme proteins, such as myoglobin, which influence the color and optical properties of meat, its spectral contribution is highly sample-specific and sensitive to muscle type and oxidation state, limiting the generalization of the model (Viljoen et al., 2007; Patel et al., 2020).

From a nutritional point of view, Fe is an essential micronutrient in the human diet, participating in oxygen transport, cellular respiration, and cognitive function (FAO, 2001; WHO, 2004). Beef is recognized as a source of highly bioavailable heme iron, whose absorption is superior to that of non-heme iron present in plant-based foods, contributing to the prevention of iron-deficiency anemia and the maintenance of adequate nutritional status (FAO, 2001; WHO, 2004). Thus, despite the observed predictive limitations, Fe maintains high relevance in the assessment of the nutritional quality of meat.

The minerals Co, Cr, and Se presented values below the detection limit of the calibration curve, making it impossible to quantify their concentrations through correlations with the spectra obtained by VIS-NIRS. This limitation is in accordance with the literature, since Bender (1992) does not report values for these elements in beef, while the USDA (2018) also does not present quantitative data for Co and Cr in 113 g portions of meat.

However, from the perspective of human health, these elements have recognized biological importance; Cobalt (Co) is part of the structure of vitamin B12, which is essential for energy metabolism and erythropoiesis; selenium acts as a component of antioxidant enzymes, such as glutathione peroxidase, and chromium has been associated with the modulation of glucose metabolism (WHO, 2004). Therefore, even when present in small concentrations and difficult to detect spectroscopically, these minerals contribute to the nutritional value of meat, reinforcing the need for complementary analytical approaches for their proper evaluation.

Micromineral metabolism in ruminants comprises intestinal absorption, systemic transport, cellular utilization, storage, and excretion, processes modulated by the chemical source of the minerals, the ruminal environment, dietary antagonisms, and the physiological state of the animal (Overton and Yasui, 2014; Spears et al., 2022). Although absorption occurs mainly in the small intestine, interactions in the rumen between minerals, microbiota, and dietary components can reduce bioavailability, especially in the presence of Mo, S, Ca, and Fe (Spears et al., 2022; Vigh et al., 2023).

Elements such as Zn, Cu, Mn, Se, and Fe perform essential functions as enzymatic cofactors involved in energy metabolism, immune response, antioxidant defense, and protein synthesis (Overton and Yasui, 2014; Narozhnykh, 2023). The Co is an integral part of vitamin B12, which is essential for energy metabolism, while Fe and Cr participate in pathways related to oxygen transport and metabolic regulation (Herdt and Hoff, 2011). The muscle deposition of these minerals depends mainly on the diet, the chemical form ingested, and food interactions (Vigh et al., 2023; Spears et al., 2024), and is also influenced by genetic and physiological factors, such as polymorphisms, age, and productive stage (Zhang et al., 2021; Hocquette, 2010).

In bovine muscle, microminerals directly affect meat quality. Heme Fe determines color stability through myoglobin (Harr et al., 2024); Cu participates in the formation and cross-linking of collagen, influencing tenderness (Chen et al., 2019) and minerals such as Se and Cu act in antioxidant systems that preserve oxidative stability during storage (Bing et al., 2022). In addition, mineral-dependent metabolic pathways can modulate the lipid composition and aromatic

profile of meat (Soret et al., 2016; Spears et al., 2024). Thus, proper nutritional management of microminerals is crucial for animal performance and for the technological, sensory, and nutritional quality of beef.

Understanding the metabolism of micro and macrominerals in bovine muscle is fundamental to improving nutritional strategies, sustaining productive performance, and ensuring the production of meat with high technological and sensory quality and nutritional value for human consumption.

For all minerals, cross-validation coefficients were consistently lower than calibration coefficients, especially for elements with less robust calibration models. This pattern reflects the lack of direct absorption features for minerals in the near-infrared region and the strong dependence of VIS-NIRS models on indirect associations with organic constituents (Schmitt et al., 2014). Furthermore, the inclusion of samples from different production systems and slaughter conditions introduces biological variability that reduces the accuracy of external prediction while increasing the robustness and practical relevance of the model (Patel et al., 2020; Savoia et al., 2020).

Overall, the results indicate that VIS-NIRS has greater potential to predict minerals closely linked to organic muscle components, such as P and S, while minerals governed by strict homeostatic control or strong ruminal antagonisms remain difficult to predict. These findings highlight the importance of integrating knowledge of ruminant mineral metabolism with spectroscopic modeling strategies to improve the assessment of beef nutritional quality (Pasquini, 2018).

VIS-NIRS is a technique that should be explored in the field of meat quality in order to reduce costs, time, and environmental pollution, given that the nutritional value of beef is becoming increasingly evident. Calibration curves for minerals in beef are capable of predicting the amount of elements in the sample; however, further studies are needed to increase the robustness of the curve and optimize mathematical models.

5. Conclusion

The results show that VIS-NIRS has good calibration capability for minerals such as P and S, moderate to poor performance for Ca, K, and Mg, and insufficient performance for Cu, Fe, Mn, and Zn. The discrepancy between the determination coefficients of calibration and prediction models indicates possible overfitting, that is, the model fits the calibration data very well, but captures not only the real patterns but also the noise or random variations of the training set, thus not maintaining performance when tested with new samples.

Although it is a promising tool for predicting mineral concentration in beef, it requires a larger number of samples and variability to increase the robustness of the calibration curve, optimizing the prediction equations and their accuracy.

Declarations

Conflict of interest: The authors declare that there is no conflict of interest.

Data Availability Declaration: Not applicable.

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Data availability

Data will be made available on request.

Animal Ethics Committee

We hereby declare that this study did not require approval from an Animal Ethics Committee. The research was conducted exclusively using beef samples obtained after slaughter, and no live animals were handled, manipulated, or subjected to any experimental procedures for the purposes of this study.

All analyses were performed on previously collected samples, and therefore the study did not involve animal experimentation, intervention, or any procedure that could cause pain, stress, or discomfort to animals. Consequently, according to ethical guidelines for animal research, studies based solely on the evaluation of biological samples obtained post-mortem do not require prior approval from an institutional animal care and use committee.

Thus, the present research complied with the ethical principles for scientific studies and did not involve procedures requiring ethical review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors declare that there are no actual or potential conflicts of interest including financial, personal, or other relationships with other people or organizations that could inappropriately influence, or be perceived to influence, this work.

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