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Anderson Bortoluzzi Moro

BIOIMPEDÂNCIA NA PREDIÇÃO DA COMPOSIÇÃO DA CARCAÇA DE CORDEIROS E DE SEUS CORTES

Santa Maria, RS
2020

Anderson Bortoluzzi Moro

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Tese apresentada ao Curso de Doutorado do Programa de Pós-Graduação em Zootecnia, Área de Concentração em Produção Animal, da Universidade Federal de Santa Maria (UFSM, RS), com requisito parcial para obtenção do grau de **Doutor em Zootecnia**.

Orientadora: Profª. Drª. Leila Picolli da Silva

Santa Maria, RS
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Aprovado em 31 de janeiro de 2020

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Santa Maria, RS
2020

DEDICATÓRIA

Ao meu pai Aldomiro e minha mãe Maria,
por todo incentivo, paciência e apoio.

Aos meus irmãos: Vagner e Vanderson,
pelo apoio e por servirem de exemplo.

Ao meu sobrinho Lucca,
por toda a alegria que trouxestes.

À minha eterna namorada Gabriele,
por todo amor, compreensão e apoio.

A todos os familiares, amigos e mestres,
que oraram por mim e que me acompanharam até aqui.

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MUITO OBRIGADO!

Não importa onde você parou,
em que momento da vida você cansou,
o que importa é que sempre é possível
e necessário "Recomeçar".

Recomeçar é dar uma nova
chance a si mesmo.
É renovar as esperanças na vida
e o mais importante: acreditar em você de novo.

Recomeçar!
Hoje é um bom dia para começar
novos desafios.

Onde você quer chegar?
Ir alto.
Sonhe alto,
queira o melhor do melhor,
queira coisas boas para a vida.
pensamentos assim trazem para nós
aquilo que desejamos.

Se pensarmos pequeno,
coisas pequenas teremos.

Já se desejarmos fortemente o melhor
e principalmente lutarmos pelo melhor,
o melhor vai se instalar na nossa vida.

(Paulo Roberto Gaefke)

RESUMO

BIOIMPEDÂNCIA NA PREDIÇÃO DA COMPOSIÇÃO DA CARCAÇA DE CORDEIROS E DE SEUS CORTES

AUTOR: Anderson Bortoluzzi Moro
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A análise de bioimpedância (BIA) voltada a análise da composição de cortes ou da carcaça de cordeiros baseia-se nos diferentes níveis de oposição à passagem de uma corrente iônica pelos seus diferentes constituintes. Neste sentido, o objetivo desta pesquisa foi avaliar o potencial da BIA em estimar a composição da carcaça de cordeiros e de seus cortes com o uso de variáveis acessórias. Trinta e um cordeiros foram abatidos em pesos pré-definidos de 20, 26, 32 ou 38 kg de peso vivo. Medidas de peso, comprimento, resistência e reatância foram coletadas nas carcaças quente e fria e nos cortes regionais (pernil, costilhar, paleta e pescoço) e no músculo *longissimus dorsi* das meias-carcaças direitas. A partir dessas medidas, outras variáveis acessórias da BIA foram calculadas. Os cortes foram desossados para obter a massa dos tecidos moles (porção comestível) dos cortes e na carcaça fria. Amostras representativas de cada corte e do músculo *longissimus dorsi* foram analisadas quimicamente, para obter a massa de umidade, minerais, proteínas, gordura e para determinar a massa magra e o conteúdo de energia bruta de cada amostra e da carcaça fria de cordeiros. A resistência, reatância, impedância, ângulo de fase, volume bioelétrico, densidade resistiva e densidade reativa foram utilizadas como variáveis independentes para predizer os constituintes dos cortes e da carcaça de cordeiros. Análises de regressão múltipla foram realizadas para calibrar os modelos de BIA. A validação cruzada *leave-one-out* foi realizada para avaliar a precisão e exatidão desses modelos. Os modelos de predição da BIA na carcaça quente e fria resultaram em 85,9% até 99,8% da variação dos constituintes da porção comestível nas carcaças de cordeiros. Os modelos de predição da BIA segmentar para estimar a composição dos próprios cortes explicaram 53,3% até 99,9% da variação de seus componentes nos cortes e 69,5% até 98,2% na carcaça de cordeiros. Já os modelos de predição da BIA no músculo *longissimus dorsi,* para estimar sua própria composição, contabilizaram em 67,5% até 99,1% na variação de seus constituintes e 82,8% até 91,7% na variação dos componentes da carcaça. As densidades resistivas ou reativas explicaram a maior parte dessa variação nos modelos de predição obtidos. Essas variáveis, juntamente com o volume bioelétrico, melhoram os modelos de predição dos componentes quantitativos na carcaça quente e fria, e foram essenciais para estimar a composição da porção comestível de cortes regionais da carcaça de cordeiros e do músculo *longissimus dorsi*. No entanto, maior precisão e exatidão são esperadas com o uso da BIA nas carcaças frias em comparação com as carcaças quentes. Adicionalmente, a paleta foi o melhor corte preditivo dos componentes comestíveis das carcaças de cordeiros através da BIA. Neste sentido, a BIA é uma técnica simples, não destrutiva, que produz resultados precisos na estimativa de componentes da carcaça de cordeiros e pode ser incorporada em centros de pesquisa e na indústria da carne de cordeiros.

Palavras-chave: composição de carne, densidade resistiva e reativa, bioimpedância elétrica, modelos de predição, ovinos

ABSTRACT

BIOIMPEDANCE TO PREDICT LAMB CARCASS COMPOSITION AND THEIR RETAIL CUTS

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ADIVISOR: Leila Picolli da Silva

Bioimpedance analysis (BIA) used to predict lamb carcass composition or their cuts is based on the different levels of opposition to the passage of an ionic current through its different constituents. Thus, the objective of this research was to evaluate the BIA potential to predict the composition of lamb carcasses and their cuts using accessory variables. Thirty-one lambs were slaughtered at predefined weights of 20, 26, 32 or 38 kg of live weight. Measurements of weight, length, resistance and reactance were collected from hot and cold carcasses and from the retail cuts (leg, rib, shoulder, and neck) and the *longissimus dorsi* muscle of the right half carcasses. From these measurements, other accessory variables of the BIA were calculated. The cuts were deboned to obtain the soft tissue mass (edible portion) of each cut and of the cold carcasses. Representative samples of each cut and of the *longissimus dorsi* muscle were chemically analyzed to obtain moisture, ash, protein, and fat masses. These compounds were used to determine the lean mass and the crude energy content of the *longissimus dorsi* muscle, of each cut and of the cold carcasses. The respective resistance, reactance, impedance, phase angle, bioelectric volume, resistive density and reactive density were used as independent variables to predict the composition of the *longissimus dorsi* muscle, the retail cuts, or the lamb carcasses. Leave-one-out cross validation was performed to assess the precision and accuracy of the predictive models. The prediction models of BIA in hot and cold carcasses resulted in 85.9% to 99.8% of the variation of the soft tissue constituents in lamb carcasses. The predictive models from the segmental BIA explained 53.3% to 99.9% of the variation of their components in the cuts and from 69.5% to 98.2% to predict the edible portion of lamb carcasses. However, the prediction models of BIA at *longissimus dorsi* muscle to estimate its own composition accounted for 67.5% to 99.1% in the variation of its constituents and for 82.8% to 91.7% in the variation of soft tissue constituents of the lamb carcasses. Resistive or reactive densities explained most of the variation in the prediction models obtained. These variables, together with bioelectric volume, improved the prediction models of the quantitative components either in hot as in cold carcasses. Furthermore, they were essential to estimate the composition of the edible portion of retail cuts from lamb carcasses and the compounds of the *longissimus dorsi* muscle. However, greater accuracy is expected with the use of BIA in cold carcasses compared to hot carcasses. Additionally, shoulder was the best predictive cut of the edible components of lamb carcasses by segmental BIA. Therefore, BIA is a simple technique, non-destructive, and it produces accurate results in predicting lamb carcass components and it might be incorporated both into research centers as in the lamb meat industry.

Keywords: bioimpedance electrical, meat composition, prediction models, resistive and reactive density, sheep

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LISTA DE ABREVIATURAS E SIGLAS

A	Minerais
AOAC	Association of Official Analytical Chemists
ARC	Agricultural Research Council
BIA	Bioimpedância
CCC	Coeficiente de correlação de concordância
Cp	Cp de Mallows
E	Energia bruta
F	Gordura
Fig.	Figura
L	Massa magra
M	Umidade
Max	Máximo
Min	Mínimo
n	Tamanho amostral
NRC	National Research Council
P	Proteínas
PA	Ângulo de fase
r	Coeficiente de correlação
R^2	Coeficiente de determinação
RMSE	Raiz do erro quadrático médio
RMSEP	Raiz do erro quadrático médio da predição
Rs	Resistência
RsD	Densidade resistiva
SBIA	Bioimpedância segmentar
SD	Desvio padrão
SEM	Erro padrão da média
ST	Tecidos moles
V	Volume bioelétrico
Xc	Reatância
XcD	Densidade reativa
Y	Variável independente
Z	Impedância

LISTA DE SÍMBOLOS

-	Menos
%	Porcentagem
+	Mais
<	Menor
=	Igual
>	Maior
±	Mais ou menos
®	Marca Registrada
°	Grau
°C	Grau Celsius
µA	Microampere
cm	Centímetro
cm^2/Ω	Centímetro quadrado/Ohm
g	Grama
Kg	Quilograma
$kg^2/cm^2\ \Omega$	Quilograma quadrado/centímetro quadrado Ohm
KHz	Quiloherts
MJ	Megajoule
mm	Milímetro
π	Pi
Ω	Ohm

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1.INTRODUÇÃO

O surgimento de consumidores cada vez mais exigentes vem destacando a importância do uso de tecnologias que garantam a sustentabilidade, biossegurança e segurança alimentar na produção animal. Combinado com maior conscientização e maiores expectativas de qualidade do produto por processadores, varejistas e consumidores, novos e complexos desafios enfrentam o setor em termos de padronização da carne ovina (SILVA *et al.*, 2018). A maneira de manter ou até aumentar a participação da carne ovina no consumo geral de carnes dependerá da diferenciação de produto, agregação de valor e do fornecimento de informações nutricionais (MONTOSSI *et al.*, 2013). As informações nutricionais são necessárias para responder à crescente preocupação dos consumidores sobre os efeitos dietéticos da carne ovina na saúde humana.

Muitos métodos estão disponíveis para avaliar a composição da carcaça de animais de produção. A classificação visual, como conformação e classes de gordura, é difícil de obter de maneira absolutamente consistente ao longo do tempo, mesmo sendo realizada por profissionais treinados. As dimensões da carcaça são os preditores mais pobres, enquanto que a dissecação da carcaça ou mesmo de cortes representativos da mesma, são mais precisas (JENKINS; LEYMASTER; TURLINGTON, 1988). As abordagens mais comuns para esse tipo de avaliação, como análises de composição física e química seguindo procedimentos laboratoriais, são destrutivas, demoradas e utilizam produtos químicos nocivos (ZANIBONI-FILHO *et al.*, 2015). Esses métodos são demorados, caros e requerem pessoal qualificado. Por esse motivo, a maioria dessas técnicas são aceitáveis por pesquisadores, porém, não são adequadas para operações comerciais ou em larga escala (FUENTES *et al.*, 2013).

No caso de cordeiros, além de análises de composição da carcaça ou de seus cortes, são realizadas análises quantitativas e qualitativas da carne por meio da avaliação de músculos específicos da carcaça. O músculo *longissimus dorsi* é normalmente utilizado nessas avaliações, devido à sua representatividade e ao seu maior tamanho em comparação com outros músculos (HASHIMOTO *et al.*, 2012; VAN HARTEN *et al.*, 2016). No entanto, o consumo de carne inclui também alguns tecidos adiposos subcutâneos e intermusculares que, na maioria das vezes, não são incluídos na análise, mas contribuem para a ingestão total de gordura na dieta (CAMPO *et al.*,

2016). Além do mais, normalmente, a compra de carne ovina é realizada após a divisão da carcaça em cortes menores, que variam de região para região. Existem diferenças na composição entre esses cortes (KEMPSTER, 1981; OWENS; DUBESKI; HANSONT, 1993). Assim, torna-se importante avaliar a composição da carcaça inteira de cordeiros, mas também de cortes menores. À medida que essas informações sobre o aspecto físico, químico e nutricional da carne são repassadas aos consumidores, estes podem adquirir carcaças ou cortes específicos, de acordo com suas preferências.

A tendência no monitoramento da qualidade da carne é mover as medições de qualidade dos laboratórios para as linhas de processamento. A identificação e o desenvolvimento de tecnologia eletrônica para prever a composição da carcaça é uma estratégia valiosa para melhorar a indústria da carne ovina (BERG *et al.*, 1996). Técnicas sofisticadas e as novas metodologias baseadas em diferentes princípios, procedimentos e/ou instrumentos são necessárias para medir diferentes atributos de qualidade da carne ovina. Do ponto de vista do consumidor, é necessário melhorar a inspeção de qualidade da carne ovina. O uso de novas tecnologias e automatização do sistema contribuem para suprir essas expectativas (VALOUS *et al.*, 2016).

Atualmente existem técnicas não invasivas e não destrutivas para avaliar a composição da carcaça e a qualidade da carne ovina. A absorciometria de raios X de dupla energia, a tomografia computadorizada e a ressonância magnética são algumas das tecnologias utilizadas que apresentam predições aceitáveis da composição da carcaça de cordeiros (GARDNER *et al.*, 2018; SCHOLZ *et al.*, 2015; XIONG *et al.*, 2017). Entretanto, seus custos elevados, baixa disponibilidade de equipamentos, o tempo despendido para coletar e processar os dados e o grau de treinamento exigido para o examinador fazer as devidas medições comprometem a incorporação de tais técnicas nos sistemas industriais existentes (MARCHELLO *et al.*, 1999). Sendo assim, essas técnicas possuem pouca aplicação prática devido às despesas de instrumentação e ao conhecimento técnico necessário durante a operação do equipamento e a interpretação dos dados. O método ideal para medir a composição da carne de cordeiro deve ser relativamente barato, exigir pouco inconveniente para o indivíduo, ser operado por técnicos não qualificados e produzir resultados altamente reprodutíveis e precisos. Entre as técnicas disponíveis, poucos métodos atendem a esses requisitos, sendo um deles, a análise da bioimpedância elétrica ou bioimpedância (BIA) (SILVA *et al.*, 2018).

A BIA voltada a análise da composição da carcaça baseia-se nos diferentes níveis de oposição à passagem de corrente iônica pelos diferentes constituintes da carcaça, que é provocada por uma diferença de potencial na amostra. Por intermédio de dois eletrodos emissores é aplicada uma corrente de excitação alternada de 800 uA em frequência única de 50 kHz. Os fluidos celulares são utilizados como resistores e as membranas celulares como capacitores elétricos. Uma queda de tensão é gerada pela impedância, ao passar pelos diferentes tecidos da carcaça, e é detectada pelos dois eletrodos receptores (BERG; MARCHELLO, 1994). A impedância de um sistema geométrico depende do comprimento do condutor, da área da seção transversal e da frequência do sinal (LUKASKI, 2013). Assumindo forma geométrica similar das carcaças de cordeiros ou de seus cortes e usando sinal elétrico constante, os componentes da impedância, resistência (Rs) e reatância (Xc) devem ser derivados em relação à composição da carcaça ou de seus cortes, respectivamente (BERG *et al.*, 1996). A impedância é baixa no tecido magro, onde principalmente o líquido intracelular e os eletrólitos estão contidos, mas é alta em tecido adiposo, uma vez que, a gordura apresenta baixa condutividade elétrica (DUNCAN *et al.*, 2007; SWANTEK *et al.*, 1992). Sendo assim, carcaças com maior quantidade de gordura devem impedir a transmissão de corrente iônica em maior extensão. A temperatura também afeta as medições de condutividade elétrica, porque a condutância (1/resistência) diminui proporcionalmente com a diminuição da temperatura (BERG *et al.*, 1997).

Nas carcaças de cordeiro é possível avaliar a impedância elétrica em toda a extensão da carcaça (COSGROVE; KING; BRODIE, 1988; JENKINS; LEYMASTER; TURLINGTON, 1988), na região dorsal da carcaça (BERG *et al.*, 1997; BERG; MARCHELLO, 1994; SILVA *et al.*, 2018; SLANGER *et al.*, 1994) e em faixas ou intervalos de frequências (ALTMANN *et al.*, 2004; HEGARTY *et al.*, 1998). O uso da espectroscopia de impedância permite avaliar a água total e também sua distribuição intra e extracelular do material biológico em teste (PLIQUETT, 2010). No entanto, apesar das vantagens teóricas do uso de múltiplas frequências, não há vantagem aparente ou significativa da espectroscopia de impedância ou em comparação com frequência única de 50 kHz, para avaliar os componentes da carcaça de cordeiros (ALTMANN *et al.*, 2004).

Através dos resultados promissores em diferentes locais de avaliação na carcaça de cordeiros, espera-se que a bioimpedância elétrica possa ser usada em cortes menores da carcaça para estimar a própria composição e a da carcaça, uma

vez que estes possam ser representativos da mesma. A análise da BIA em segmentos ou em pequenos cortes da carcaça, configuram a análise de bioimpedância segmentar. Essa análise é comumente usada em humanos para melhor estimar determinado componente físico ou químico de interesse, por avaliação local ou pela soma desse componente avaliado em diferentes partes do corpo (WARD, 2012). Limitações da medição da bioimpedância de corpo inteiro na avaliação de compartimentos de segmentos corporais deram origem à demanda por aplicações de análise de bioimpedância localizada por segmento (KHALIL; MOHKTAR; IBRAHIM, 2014).

Neste sentido, a BIA tem excelente potencial para prever a composição da carcaça e de seus cortes em situações comerciais, dada sua simplicidade. Um sistema para o uso da BIA pode ser facilmente incorporado às plantas industriais de carnes existentes. Uma vez adaptada aos computadores *on-line*, essa técnica pode produzir rapidamente uma estimativa da massa magra da carcaça de cordeiros (BERG; MARCHELLO, 1994). Esse sistema pode ser benéfico, pois não requer indivíduo especialmente qualificado para sua operação e pode ser mais rápido, barato e preciso do que outras técnicas existentes (SILVA *et al.*, 2018). No entanto, a BIA não é um método direto de avaliação da composição da carcaça ou de seus cortes e a sua precisão depende em grande parte do uso de equações de regressão apropriadas (NORMAN *et al.*, 2012).

A BIA foi utilizada para prever a composição corporal em diferentes espécies, como em bubalinos (SARUBBI; BÀCULO; BALZARANO, 2008), bovinos (MARCHELLO *et al.*, 1999; SCHÄFF *et al.*, 2017) e ovinos (ALTMANN *et al.*, 2004; AVRIL *et al.*, 2013). No entanto, devido a precisão da técnica não estar bem definida, estudos mais avançados devem ser conduzidos. Algumas variáveis como densidades resistivas e reativas, que envolvem a relação entre peso e comprimento com a resistência ou reatância das carcaças, respectivamente, foram usadas como variáveis preditoras nas carcaças de bovinos (ZOLLINGER *et al.*, 2010) e em cordeiros (MORO *et al.*, 2019a, 2019b). Até o vigente período, essas variáveis ainda não foram testadas em carcaças de cordeiro, nem em cortes menores. Sendo assim, espera-se que essas novas variáveis possam melhorar modelos bioestatísticos de predição da composição da porção comestível da carcaça de cordeiros. Neste sentido, há necessidade de aprofundamento de pesquisas sobre a eficiência da análise da BIA nas carcaças quente e fria, assim como em cortes menores da carcaça de cordeiros.

Adicionalmente, é necessário avaliar a potencialidade dessas novas variáveis da BIA nesses cortes e no músculo *longissimus dorsi* com o propósito de produzir informações qualitativas e quantitativas da carne de cordeiro, de maneira rápida, objetiva e precisa. Também, para avaliar o potencial da BIA como alternativa aos métodos tradicionais de análise de composição da carcaça ou da carne de cordeiros.

1.1 OBJETIVOS

1.1.1 Objetivo Geral

Avaliar o potencial da bioimpedância em estimar a composição da carcaça de cordeiros e de seus cortes com o uso de variáveis acessórias.

2.1.1 Objetivos Específicos

- Investigar o potencial da análise de BIA, nas carcaças quente e fria, utilizando medidas acessórias, como a densidade resistiva e a densidade reativa, no processo de modelagem para determinar a composição da porção comestível das carcaças de cordeiros.
- Analisar a potencialidade da análise de BIA segmentar na predição da composição da porção comestível de cada corte regional da carcaça e selecionar o melhor corte preditor da composição da carcaça de cordeiro.
- Testar a BIA como alternativa aos métodos tradicionais utilizados na avaliação da composição da carne de cordeiro e usar o músculo *longissimus dorsi* como indicador da composição da carcaça de cordeiros.

2. ARTIGO 1 - ASSESSING THE COMPOSITION OF THE SOFT TISSUE IN LAMB CARCASSES WITH BIOIMPEDANCE AND ACCESSORY MEASURES[1]

[1] Artigo submetido para a revista Meat Science (https://www.elsevier.com/journals/meat-science/0309-1740/guide-for-authors). O comprovante de submissão está disposto no Anexo I.

Assessing the composition of the soft tissue in lamb carcasses with bioimpedance and accessory measures

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Abstract

Consumers are demanding additional information to support their decision-making while shopping for meat. In the lamb industry, labelling carcasses with composition information is challenging. This is due to issues with conventional analytical

procedures, such as the time spent with determinations and product loss or devaluing due to sampling for analysis. The objective was to evaluate the potential use of bioimpedance analysis (BIA) to determine composition of the soft tissue portion of lamb carcasses. Thirty-one Texel and Ile-de-France crossbreed ram lambs were slaughtered at 20, 26, 32, or 38 kg of body weight. Values of resistance and reactance were collected from hot and cold carcasses, which weighed 12.4 ± 2.99 kg and 11.9 ± 2.94 kg, respectively and measured 53.9 ± 3.25 cm of length. Carcass weight and length were used to calculate other BIA variables such as impedance modulus, phase angle, bioelectrical volume, and both resistive and reactive densities. These variables were used as independent variables to predict the contents of soft tissue, moisture, ash, protein, fat, lean, and crude energy of the carcasses. Multiple regression analyses were carried out to calibrate BIA models. The leave-one-out cross-validation was performed to evaluate precision and accuracy of the BIA technique. Resistive density was the most important BIA variable to predict lamb composition of hot carcasses, which explained 83% to 92% of the variation in composition. In turn, reactive density better predicted lamb carcass composition in cold carcasses, which accounted for 81% to 92% of their variation in carcass composition. In addition, prediction models of the soft tissue portion of lamb carcasses assessed on cold carcasses showed a higher coefficient of determination and smaller root mean square error and Mallows Cp values than hot carcasses. Therefore, BIA has an excellent potential to predict lamb carcass components on either hot as cold carcass; however, higher accuracy was found with cold carcasses in comparison with hot.

Keywords: carcass composition, cold carcass, electrical impedance, fat, hot carcass, lean

1. Introduction

Improvements in the lamb industry, including better farm management practices, genetic selection, and consumer-focused production, have contributed to the production of heavier and leaner carcasses (Montossi *et al.*, 2013). A better understanding of consumer preference and perception about meat quality has been a driving factor to improve the competitiveness of the meat industry (Font-i-Furnols & Guerrero, 2014). However, the meat industry faces challenges promoting awareness about the attributes of lamb to new consumers (de Andrade, de Aguiar Sobral, Ares, & Deliza, 2016). Strategies to assess flesh composition, such as the amounts of lean and fat, could allow for labelling carcasses and respective cuts with accurate and detailed information. Furthermore, this detailed information could assist the sorting of carcasses for further processing or the fresh lamb market. Moreover, this information could be used to provide feedback to the production sector, contributing to subsequent improvements in the lamb production chain.

Methods for assessing carcass composition are expected to be precise, accurate, inexpensive, practical, and fast to apply (Stanford, Jones, & Price, 1998). Techniques, such as dual-energy X-ray absorptiometry, computed tomography, and magnetic resonance imaging, have provided exemplary predictions of carcass and body composition (Gardner *et al.*, 2018; Scholz, Bünger, Kongsro, Baulain, & Mitchell, 2015; Xiong, Sun, Pu, Gao, & Dai, 2017). However, these techniques are currently expensive to implement and may be time consuming; therefore, their adoption is limited in commercial packing plant settings (Silva *et al.*, 2018).

Bioimpedance analysis (BIA) measures opposition to the flow of an electrical current through carcass fluids. In brief, the electrical current passes across the carcass, and a voltage drop represents an impedance (Berg & Marchello, 1994). Lean tissue is highly conductive, whereas fat tissue has insulation properties (Lukaski, Johnson, Bolonchuk, & Lykken, 1985). Impedance readings are affected by carcass temperature (Berg, Neary, Forrest, Thomas, & Kauffman, 1996). Bioimpedance has been used to predict composition in buffalo (Sarubbi, Bàculo, & Balzarano, 2008), cattle (Marchello, McLennan, Dhuyvetter, & Slanger, 1999; Schäff *et al.*, 2017), and sheep (Avril, Lallo, Mlambo, & Bourne, 2013; Berg & Marchello, 1994; Silva *et al.*, 2018), but the accuracy of bioimpedance may be improved by including other variables.

Resistive and reactive densities, which involve the relationship between either body or carcass length with resistive or reactive measurements, respectively, were used as predictors of cattle carcass (Zollinger, Farrow, Lawrence, & Latman, 2010) and lamb body (A. B. Moro *et al.*, 2019; Anderson B. Moro *et al.*, 2019) compositions. However, there is a lack of studies reporting similar predictions for lamb carcasses. Therefore, we hypothesized that resistive and reactive densities could improve the accuracy of the bioimpedance technique for determinations in both hot and cold carcasses. The objective of this study was to evaluate the potential of improving the bioimpedance analysis using accessory measures in the modelling process to determine the composition of the soft portion of hot and cold lamb carcasses.

2. Material and Methods

2.1. Animal management and carcass evaluation

All procedures involving animals were reported by Anderson B. Moro *et al.* (2019) and were approved by the Ethics Committee on Animal Research of the Universidade Federal de Santa Maria, Brazil. Briefly, thirty-two Texel and Ile de France crossbred ram lambs, weaned at 90 days of age, were used. The lambs were distributed across eight collective pens with four lambs per pen, according to similarity in their initial body weight. The animals were fed *ad libitum,* and the amount of feed offered was adjusted daily to keep the refusals at 10%. The diet was formulated according to the NRC (2007) to ensure a 200 g daily weight gain. Body weight was measured weekly, until lambs reached pre-established slaughter weights of 20, 26, 32, or 38 kg.

Animals were slaughtered after 14 hours of feed withdraw with free access to water. Carcasses were weighed and stored in a cooler at 2ºC for 24 hours, which was followed by re-weighing. Before and after chilling carcasses, temperature was measured at the loin region, between the fourth and fifth lumbar vertebra (Osório *et al.*, 1998) using a digital thermometer (model HI99163, Hanna Instruments, Villafranca Padovana, Italy). Carcass length was measured with a tape measure, as the maximum distance between the anterior border of the first rib at its midpoint and the anterior edge of the ischio-pubic symphysis (Osório *et al.*, 1998). Bioimpedance measurements were obtained on hot and cold carcasses after weighing the carcasses.

2.2. Bioimpedance measurements

A thorough description of the BIA device and of the technique was described by Anderson B. Moro *et al.* (2019). In summary, a single-frequency BIA instrument (model Quantum II, RJL Systems, Detroit, USA) was used. A sinusoidal current of 800 µA at 50 kHz was applied to the carcass tissue, and the resulting voltage was measured.

Then, resistance and reactance values were calculated. The technique used four electrodes connected to the carcass by color-coded clips. There were two black and two red electrodes that were configured as current and pick-up, respectively. Data were collected following the method of Jenkins, Leymaster, & Turlington (1988). Briefly, carcasses were positioned on their right side and laid on plastic tarpaulin for insulation. The current electrodes were attached to the extensor muscle complex of the front and rear limbs and placed in the muscles approximately 3 cm proximal to the carpal and tarsal articulations, respectively. The pick-up electrodes were inserted 10 cm away from the current electrodes, caudal to the knee region (rear limb) and cranial to the elbow region (front limb). The electrodes were stainless steel needles with a spiral cable (0.25 x 50 mm).

Based on resistance (Rs, Ω) and reactance (Xc, Ω) values of hot and cold carcasses, the value of the impedance modulus (Z, Ω) was calculated using the formula proposed by Lukaski *et al.* (1985). Phase angle (PA, º) was calculated from the relationship between the arch tangent of reactance and resistance, and to convert the radian values into degrees, the PA values were multiplied by 180º/π (Lukaski, 2013). The bioelectrical volume (V, cm^2/Ω) was calculated as the relationship between the squared carcass length and resistance (Jenkins *et al.*, 1988). Resistive density (RsD, kg^2/cm^2 Ω) and reactive density (XcD, kg^2/cm^2 Ω) were calculated using the equations described by Zollinger *et al.* (2010) with adaptations: RsD = carcass $weight^2$/(carcass $length^2$/Rs) and XcD = carcass $weigth^2$/(carcass $length^2$/Xc) for hot and cold carcasses, respectively.

2.3. Laboratory analysis

After the BIA data were collected, cold carcasses were longitudinally split into two halves. The right half of the carcass was weighed and divided into four cuts (neck, shoulder, rib, and leg). Bones were removed from all cuts in order to determine soft tissue mass of the half carcass. The soft tissue sample obtained from each cut, was homogenized, and submitted to laboratory analysis. Moisture (930.15), protein (992.15), and ash (942.05) were determined according to AOAC (1995) methods. Fat was determined according to the method proposed by Bligh & Dyer (1959). Crude energy content was obtained using caloric equivalents of fat and protein according to the ARC (1980). The moisture, ash, protein, fat, and crude energy contents of each cut were used to determine the half carcass composition, and then, values were adjusted to the cold carcass weight. The lean content of the carcass was calculated as the sum of protein and moisture contents of the soft tissue (Jenkins *et al.*, 1988).

2.4. Statistical analysis

One lamb died during the feeding trial; therefore, a dataset of 31 lambs was available for all statistical analyses, which were performed using the Minitab software (v.17.1.0, Minitab Inc., State College, PA, USA). A descriptive statistical analysis was performed to characterize the database, and correlation coefficients between the BIA measurements of hot and cold carcasses and the components of the soft tissue portion of the carcasses were determined. Additionally, analyses of variance were performed to compare the BIA values measured on either hot or cold carcasses. The model for this last procedure included the fixed effect of carcass (hot or cold) and body weight was a co-variable. The potential differences between variables measured on hot and cold carcasses were evaluated through the *F* test.

For the multiple regression analyses, the soft tissue fraction of the lamb carcasses were the dependent variables, and bioimpedance measurements were the independent variables. Stepwise regression was used to determine the best predictors of the models. A. B. Moro *et al.* (2019) brings a detailed description of the regression analysis applied in this study. Briefly, the models were selected by the highest coefficient of determination (R^2), lowest root mean square error (RMSE), and the Mallows Cp statistic (Cp) closest to the number of parameters included in the model. Outliers were identified by plotting studentized residuals against the predicted values and by evaluating Cook's D coefficients.

Predictive performance of the models was assessed using the leave-one-out cross-validation method. Thus, one carcass was selected from the complete dataset, and regression parameters were estimated with the data from the remaining n − 1 carcasses. Values of soft tissue, moisture, ash, protein, fat, lean, and crude energy were predicted for the selected carcass by this regression function. The coefficient of determination (R^2), the root mean squared error of prediction (RMSEP), and concordance correlation coefficient (CCC) were assessed to measure precision and accuracy of the models by comparing predicted and observed values, according to Tedeschi (2006). Data were considered statistically significant when $P < 0.05$ for all statistical analyses.

3. Results

3.1. Descriptive statistic and mean comparisons between BIA measurements of hot and cold carcasses

The sample size, minimum, maximum, mean, and standard deviation of the BIA measurements and the soft tissue components of lamb carcasses are shown in Table 1. Hot and cold carcass weights ranged from 6.76 to 17.8 kg and from 6.36 to 17.4, respectively. Most of the carcass weight was composed of soft tissue, ranging from 5.07 to 14.6 kg. The fattiest carcass had 2.53 kg of fat, while the leanest had 0.49 kg of fat. Carcass length varied from 47.5 to 60.0 cm. Mean comparison of the BIA parameters is shown in Table 2. Resistance and reactance values measured on cold carcasses were higher than when measured on hot carcasses. The same was observed with other BIA parameters, except bioelectrical volume, which was 3.49 times higher in hot carcasses.

3.2. Correlations between BIA measurements and soft tissue components of lamb carcass

Correlations of PA, V, RsD, and XcD with all components of the soft tissue portion of the carcass (moisture, ash, protein, fat, lean, and crude energy) were positive, regardless if BIA parameters were measured on hot or cold (Table 3) carcasses. Interestingly, soft tissue components had increased correlations with RsD than with XcD when BIA parameters were measured on hot carcasses, while measuring BIA on cold carcasses resulted in an opposite pattern. Similar discrepancies between BIA measured on hot and cold carcasses were found for Rs, Xc, and Z parameters. While soft tissue components were correlated with Xc, they were not correlated ($P > 0.05$) with both the Rs and Z measures on hot carcasses. The opposite was observed when BIA parameters were measured on cold carcasses; Rs and Z were correlated with all soft tissue components, but correlations with Xc were not significant ($P > 0.05$).

3.3. Prediction models for lamb carcass composition

Models to predict composition of the edible portion of lamb carcasses are shown in Table 4. Using BIA parameters measured on a hot carcass, RsD accounted for 91.92% of the variation of soft tissue weight. By adding V, PA, XcD, and Xc in the model, the explained variance increased to 99.56, 99.70, 99.75, and 99.80%, respectively. The cross-validation assessment showed that inaccuracy of predicting soft tissue weight using BIA measures on hot carcass was only 151 g. Further, moisture, ash, protein, and lean mass weights were explained most by RsD, which accounted for 88.5, 83.5, 88.8, and 88.5 of their variances, respectively. Bioelectrical volume was the only other variable that contributed to explain the variances of those components. In turn, 98.5% of the variance in fat content was explained by XcD and V measured on a hot carcass, while the model to predict crude energy content of the soft tissue portion of the carcass included RsD, V, and PA. Inaccuracy of these last models was estimated at 169 g and 6.8 MJ, respectively.

Using the BIA data measured on cold carcasses, RsD and V were the only variables included in the models to predict ash and protein content of the edible portion of the carcass. However, different models were built for predicting the other carcass components, with XcD as the most important variable. Despite these differences, in general, models using BIA data measured on cold carcasses were more accurate than models using BIA collected from hot carcasses.

4. Discussion

According to Jenkins *et al.* (1988), bioimpedance may represent a practical and fast procedure to predict carcass composition that would be highly appealing for commercial applications. Bioimpedance must produce accurate predictions in a wide range of carcass sizes to reflect the variety of the carcasses at the packing plants. In our study, the weight and composition ranges of the lamb carcasses were considerable, resulting in substantial variation in the BIA readings.

The BIA measurements were affected by carcass temperature. As expected, resistance and reactance were considerably higher for cold carcasses than hot carcasses because conductance decreases proportionally with decreasing temperature (Berg & Marchello, 1994). The decreased conductance occurs in response to the loss of fluids during cooling and changes in the distribution of electrolytes between intracellular and extracellular media in the tissues (Marchello *et al.*, 1999; Slanger *et al.*, 1994). Electrical conductance of an organism is determined by its water and solute contents (Duncan *et al.*, 2007). Berg & Marchello (1994) reported differences of 154 and 30 Ω from cold to hot lamb carcasses, which represent 2.38 and 2.46 times increase for Rs and Xc, respectively. Similar results were recorded by Berg, Neary, Forrest, Thomas, & Kauffman (1997), where these authors reported an increase of 2.16 and 2.93 times increase for Rs and Xc, from hot and cold carcasses, respectively. These results were slightly lower than observed in our study, which could be due to minor differences in experimental settings.

Although temperature influenced differences between BIA readings on hot and cold carcasses, the magnitude and significance of the correlations were similar. Resistance and reactance had weak correlations with most carcass components. Similar correlations between resistance and reactance with carcass components were reported in beef (Zollinger *et al.*, 2010) and pigs (Swantek, Crenshaw, Marchello, &

Lukaski, 1992). Other lamb carcass studies involving BIA accounted for 79% and 78% of the variation in the weight of the fat-free soft tissue (Berg & Marchello, 1994) and for 72% and 77% of the variation in lean mass (Berg *et al.*, 1997) in hot and cold carcasses, respectively. These authors (Berg & Marchello, 1994 and Berg *et al.*, 1997) used the weight of cold or hot carcasses, resistance, reactance, carcass length, and temperature as independent variables in their models. In our study, Rs and Xc were used to derive other electrical property equations, such as PA, V, RsD, and XcD, which resulted in stronger correlations and improved the potential for estimating lamb carcass composition. This happens because mass and length of a carcass affect the electrical current flow through the carcass. Hartman *et al.* (2015) stated that derived electrical equations represent a set of candidate variables that can be used to predict water, fat, protein, and crude energy content of the soft tissue portion of a carcass using standard linear modeling methods.

We observed that RsD and XcD measured on hot and cold carcasses, respectively, were the most important predictors of the composition of the soft tissue portion of the carcasses. Zollinger *et al.* (2010) reported that, although RsD was the single best predictor variable for trimmable fat (54%) and salable carcass yield (44%), it was not included into the best fit model for predicting trimmable fat. Typically, electrical conductivity is greater in lean tissue than fat due to its higher water and electrolyte contents (Duncan *et al.*, 2007). Progressive degradation of cell membranes explains the changes in resistance over 24 h post-mortem (Altmann & Pliquett, 2006). In turn, reactance measures a total cell volume and should be related to the size and condition of the subject (Hafs & Hartman, 2011). Therefore, the effect of cooling the carcass on these cell characteristics may explain why XcD is more important than RsD for predicting carcass composition when BIA was measured on cold carcasses rather than

hot carcasses. Bioelectrical volume was correlated with all carcass components, regardless of being measured on hot or cold carcass, and it was included in all prediction models. We reported that bioelectrical volume was essential to predict the weights of soft tissue (A. B. Moro *et al.*, 2019), as well as moisture, protein, fat, and lean mass (Anderson B. Moro *et al.*, 2019) of lamb carcasses by *in vivo* bioimpedance analysis. The inclusion of phase angle contributed to the estimated soft tissue content of a hot carcass, fat amount of a cold carcass, and the determination of crude energy content of both hot and cold carcasses.

Mallows' Cp statistic was used to evaluate the regression models for carcass composition. A Mallows' Cp value that is close to the number of predictors plus the constant indicates that the model is relatively unbiased for estimating the true regression coefficients and predicting future responses (Slanger & Marchello, 1994). However, cross-validation studies are needed to substantiate the predictability of the procedure for lamb carcasses in varying conditions at abattoirs. Thus, to evaluate the fit of these models for each data set, a leave-one-out validation approach using prediction sum of squares residuals was used, as described by Hafs & Hartman (2011). These residuals were estimated by leaving a single observation out and calculating a residual by subtracting the observed value from that predicted by the regression model predicted with the remaining observations. These observations were compared with the residuals estimated from the overall means model producing an R^2 of prediction to indicate the overall predictive performance. The level of accuracy and precision required must be considered in conjunction with the associated cost (Jenkins *et al.*, 1988). The CCC statistic indicated that the model with the value closest to 1 was the more accurate model to predict the dependent variable.

Regardless of differences between models using BIA variables measured on hot or cold carcass, bioimpedance was a precise and accurate technique to estimate the soft tissue composition of lamb carcasses. The advantage to assessing BIA on cold carcass is that the loss of weight from hot to cold carcass depends on several factors such as carcass management, uniformity and thickness of back fat, and chilling temperature (dos Santos *et al.*, 2019). Thus, BIA measurements on cold carcasses might offset these possible factors. Moreover, cold carcass assessments better represent the real composition of the marketable soft tissue portion. However, all segments of the meat industry can use this technology, and its use could lead to the development of carcass merit payment programs (Marchello *et al.*, 1999).

Bioelectrical impedance was minded for practical application, being capable of incorporation and use in a system where the degree of operator training required would be minimal. With further refinement of the technique and a better system for weight and length measurements, faster results could be achieved. For packing plants, all measurements need to take less than 10 seconds per carcass, have minimal effects of manual service during reading and processing values, and the instrument needs to relate to a computer to automate the entire measurement process. As a result, BIA can be applied in packing plants to quickly determine the accurate composition of lamb carcasses, which will relate to the composition of the cuts that consumers will be purchasing from the grocery stores. The information provided by BIA will to respond to the increased concerns of consumers about dietary effects on health related to meat composition (Jenkins *et al.*, 1988). Therefore, a labeled lamb with precise composition could fill a niche market for informed human nutrition utilization, which will be improved when this technique is further refined for assessing the composition of retail cuts.

5. Conclusion

Bioimpedance is a fast, relatively inexpensive, practical, accurate, and non-destructive technique to predict important parameters of the soft tissue portion of lamb carcasses. The use of resistive and reactive density and bioelectrical volume was essential to improving the accuracy of the prediction models of the soft tissue portion composition from lamb carcasses. Bioimpedance analysis has excellent potential to be used on hot and cold carcasses. However, BIA measurements obtained from a cold carcass predict the lamb carcass components with higher accuracy than those obtained from hot carcasses.

Conflict of interests

All authors have no conflict of interest to declare.

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Table 1: Descriptive statistics of bioimpedance analysis (BIA) of hot and cold carcasses and composition of the soft tissue portion of lamb carcasses.

Variables	n[a]	Min[b]	Max[c]	Mean	SD[d]
Hot carcass					
Hot carcass weight, kg	31	6.76	17.8	12.4	2.99
Temperature, ºC	31	26.3	31.4	29.7	1.42
Resistance, Ω	31	172.0	277.0	232.2	22.4
Reactance, Ω	31	23.0	51.0	36.5	7.05
Impedance, Ω	31	174.1	281.7	235.1	22.9
Phase angle, º	31	6.76	11.2	8.91	1.27
Bioelectric volume, cm^2/Ω	31	9.52	18.9	12.7	1.97
Resistive density, $kg^2/cm^2\ \Omega$	31	4.79	22.2	12.4	4.70
Reactive density, $kg^2/cm^2\ \Omega$	31	0.59	4.41	2.04	1.02
Cold carcass					
Cold carcass weight, cm	31	6.36	17.4	11.9	2.94
Temperature, ºC	31	2.00	11.6	7.16	2.47
Resistance, Ω	30	623.0	1569.0	850.5	221.2
Reactance, Ω	30	124.0	232.0	185.9	22.8
Impedance, Ω	30	645.5	1584.9	871.3	219.3
Phase angle, º	30	8.12	15.4	12.8	2.28
Bioelectric volume, cm^2/Ω	30	1.66	5.22	3.65	0.96
Resistive density, $kg^2/cm^2\ \Omega$	30	18.9	62.8	40.1	12.9
Reactive density, $kg^2/cm^2\ \Omega$	30	3.15	16.3	9.34	3.94
Carcass length, cm	31	47.5	60.0	53.9	3.25
Cold carcass composition					
Bone weight, kg	31	1.29	2.78	2.20	0.39
Soft tissue weight, kg	31	5.07	14.6	9.71	2.58
Moisture, kg	31	3.55	8.59	6.16	1.33
Ash, kg	31	0.05	0.13	0.09	0.02
Protein, kg	31	0.98	2.65	1.83	0.47
Fat, kg	31	0.49	2.53	1.39	0.64
Lean, kg	31	4.53	11.1	7.94	1.77
Crude energy, MJ	31	42.4	157.6	96.7	35.0

[a]n = Sample size; [b]Min = Minimum; [c]Max = Maximum; [d]SD = Standard deviation.

Table 2 Comparison of averages of bioimpedance values measured on hot and cold lamb carcasses.

Variables	Hot carcass	Cold carcass	SEM[1]	*P*-value
Carcass weight, kg	12.4	11.9	0.09	< 0.0001
Temperature, ºC	29.7	7.16	0.24	< 0.0001
Resistance, Ω	231.7	851.0	29.2	< 0.0001
Reactance, Ω	36.6	185.9	2.21	< 0.0001
Impedance, Ω	234.6	871.8	29.1	< 0.0001
Phase angle, º	8.92	12.8	0.19	< 0.0001
Bioelectric volume, cm^2/Ω	12.7	3.64	0.13	< 0.0001
Resistive density, $kg^2/cm^2\ \Omega$	12.5	40.1	0.90	< 0.0001
Reactive density, $kg^2/cm^2\ \Omega$	2.06	9.32	0.17	< 0.0001

[1]SEM = Standard error of mean

Table 3 Correlation matrix between bioimpedance measurements from hot (above diagonal) and cold (below diagonal) carcasses and composition of the soft tissue portion of lamb carcasses.

Variables[1]	Rs, Ω	Xc, Ω	Z, Ω	PA, º	V, $cm^2/Ω$	RsD, kg^2/cm^2 Ω	XcD, kg^2/cm^2 Ω	ST, kg	M, Kg	A, Kg	P, kg	F, Kg	L, Kg	E, MJ
Rs, Ω	-	0.674***	0.999***	0.217	-0.597***	0.14	0.177	-0.093	-0.135	0.009	-0.118	-0.027	-0.139	-0.112
Xc, Ω	0.524**	-	0.700***	0.864***	-0.025	0.750***	0.797***	0.590***	0.539**	0.606***	0.563***	0.622***	0.536**	0.565***
Z, Ω	1.000***	0.539**	-	0.251	-0.579***	0.171	0.209	-0.062	-0.106	0.038	-0.088	0.003	-0.11	-0.082
PA, º	-0.810**	0.041	-0.799***	-	0.371*	0.892***	0.930***	0.841***	0.817***	0.796***	0.821***	0.846***	0.816***	0.831***
V, $cm^2/Ω$	-0.895***	-0.315	-0.891***	0.865***	-	0.522**	0.463**	0.736***	0.723***	0.620***	0.757***	0.650***	0.731***	0.712***
RsD, kg^2/cm^2 Ω	-0.079	0.511**	-0.067	0.446*	0.365*	-	0.990**	0.959***	0.941***	0.914***	0.942***	0.935***	0.941***	0.937***
XcD, kg^2/cm^2 Ω	-0.404*	0.366*	-0.391*	0.734***	0.630***	0.929**	-	0.933***	0.906***	0.891***	0.913***	0.919***	0.905***	0.913***
ST, kg	-0.564***	0.152	-0.554**	0.796***	0.736***	0.850***	0.961***	-	0.994***	0.918***	0.993***	0.969***	0.996***	0.985***
M, Kg	-0.566***	0.165	-0.556**	0.777***	0.723***	0.806***	0.956***	0.996***	-	0.914***	0.987***	0.942***	0.999***	0.960***
A, Kg	-0.484**	0.194	-0.474**	0.691***	0.620***	0.826***	0.899***	0.923***	0.916***	-	0.920***	0.845***	0.916***	0.886***
P, kg	-0.546**	0.151	-0.536**	0.781***	0.757***	0.854***	0.953***	0.993***	0.987***	0.924***	-	0.949***	0.993***	0.972***
F, Kg	-0.554**	0.117	-0.545**	0.760***	0.650***	0.787***	0.926***	0.968***	0.959***	0.876***	0.947***	-	0.946***	0.995***
L, Kg	-0.560**	0.158	-0.550**	0.775***	0.731***	0.819***	0.958***	0.997***	0.999***	0.917***	0.993***	0.953***	-	0.965***
E, MJ	-0.556**	0.123	-0.547**	0.769***	0.712***	0.808***	0.942***	0.986***	0.976***	0.897***	0.973***	0.995***	0.974***	-

[1]Rs = Resistance; Xc = Reactance; Z = Impedance; PA = Phase angle; V = Bioelectrical volume; RsD = Resistive density; XcD = Reactive density; ST = Soft tissue; M = Moisture; A = Ash; P = Protein; F = Fat; L = Lean; E = Crude energy.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

Table 4 Prediction models of lamb carcass composition through bioimpedance analysis on hot and cold carcasses.

	Models[1]	Calibration				Cross-validation		
		R^{2a}	RMSE[b]	Cp[c]	*P*-value	R^{2a}	RMSEP[d]	CCC[e]
Bioimpedance analysis on hot carcass								
Soft tissue, kg	*Y* = - 2.812 + 0.5435RsD + 0.3712V + 0.4159PA - 0.780XcD - 0.0288Xc	0.998	0.125	5.76	< 0.0001	0.996	0.151	0.998
Moisture, kg	*Y* = 0.366 + 0.2381RsD + 0.2361V	0.980	0.194	18.3	< 0.0001	0.975	0.208	0.987
Ash, kg	*Y* = 0.0244 + 0.0032RsD + 0.0018V	0.863	0.007	1.42	< 0.0001	0.820	0.008	0.904
Protein, kg	*Y* = - 0.1937 + 0.0748RsD + 0.0866V	0.984	0.060	8.82	< 0.0001	0.981	0.064	0.990
Fat, kg	*Y* = - 0.972 + 0.1091V + 0.5072XcD	0.947	0.146	0.99	< 0.0001	0.920	0.169	0.958
Lean, kg	*Y* = 0.1600 + 0.3142RsD + 0.3226V	0.985	0.223	24.9	< 0.0001	0.981	0.238	0.991
Crude energy, MJ	*Y* = - 82.50 + 5.053RsD + 6.391V + 4.430PA	0.972	6.220	1.70	< 0.0001	0.960	6.849	0.980
Bioimpedance analysis on cold carcass								
Soft tissue, kg	*Y* = 0.738 + 0.1840XcD + 1.2148V + 0.0918RsD - 0.0046Xc	0.997	0.162	3.26	< 0.0001	0.995	0.180	0.998
Moisture, kg	*Y* = 0.915 + 0.1096XcD + 0.6906V + 0.0461RsD	0.991	0.135	2.57	< 0.0001	0.988	0.149	0.994
Ash, kg	*Y* = 0.0165 + 0.0088V + 0.0010RsD	0.859	0.007	0.56	< 0.0001	0.824	0.008	0.905
Protein, kg	*Y* = - 0.1166 + 0.2684V + 0.0242RsD	0.982	0.065	1.95	< 0.0001	0.978	0.070	0.989
Fat, kg	*Y* = - 0.145 + 0.1465XcD + 0.3488V - 0.0795PA	0.940	0.167	0.80	< 0.0001	0.908	0.193	0.952
Lean, kg	*Y* = 1.008 + 0.1418XcD + 0.9131V + 0.0615RsD	0.992	0.177	1.39	< 0.0001	0.988	0.192	0.994
Crude energy, MJ	*Y* = 12.24 + 8.302XcD + 19.71V - 4.700PA	0.972	6.299	0.68	< 0.0001	0.951	7.773	0.975

[a]R^2 = Coefficient of determination; [b]RMSE = Root mean squared error; [c]Cp = Mallows Cp statistic; [d]RMSEP = Root mean squared error of prediction; [e]CCC = Concordance correlation coefficient.

[1]*Y* = Independent variable; RsD = Resistive density; V = Bioelectrical volume; PA = Phase angle; XcD = Reactive density; Xc = Reactance.

3. ARTIGO 2 - SEGMENTAL BIOIMPEDANCE ANALYSIS FOR ESTIMATING THE EDIBLE COMPONENTS IN RETAIL CUTS AND CARCASSES OF LAMBS[2]

[2] Este artigo foi elaborado de acordo com as normas da revista Food Control (https://www.elsevier.com/journals/food-control/0956-7135/guide-for-authors).

Segmental bioimpedance analysis for estimating the edible components in retail cuts and carcasses of lambs

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Abstract

The objective of this study was to evaluate the potentiality of segmental bioimpedance analysis (SBIA) to predict the edible components of each retail cut and assess the best predictor cut of lamb carcass composition. Thirty-one chilled carcasses from Texel and Ile de France crossbred lambs were used. The right half carcasses were weighed and then divided into four retail cuts: leg, rib, shoulder, and neck. The weighed, length, resistance (*Rs*) and reactance (*Xc*) were measured in all cuts. From these primary records other equations were derived, such as impedance modulus (*Z*), phase angle (*PA*), bioelectrical volume (*V*), resistive density (*RsD*), and reactive density (*XcD*). Representative samples of the edible portion of each cut were chemically analyzed to determine its composition and, by addition, the whole carcass composition. Multiple regression analyses were performed and the predictive performance of the models was assessed by using the leave-one-out cross-validation method. Resistive and reactive densities, followed by bioelectrical volume, explained most of the variation of all components evaluated in individual cuts and in carcasses. The best predictive models were found for soft tissue in all cuts (R^2 = 0.99). Lean was the second best predictive variable on leg (R^2 = 0.98) and neck (R^2 = 0.97), whereas, protein was the second one on rib (R^2 = 0.98) and shoulder (R^2 = 0.96). Predicting models of fat and

crude energy, for all cuts, showed R^2 ranging from 0.83 to 0.92 and 0.90 to 0.97, respectively. Ash and soft tissue were the parameters on carcass that showed, respectively, the lowest and highest accuracy for SBIA in all carcass cuts. Therefore, SBIA might be used easily in practice and serve to evaluate the composition of small cuts and/or lamb carcasses. Additionally, shoulder was the best predictor cut of the edible components of lamb carcasses by segmental bioimpedance analysis.

Keywords: impedance, lamb, meat quality, resistive density, soft tissue composition

Highlights

- Segmental bioimpedance predicts accurately retail cuts' components of lamb carcasses.
- Lamb carcass composition can be assessed by segmental bioimpedance analysis.
- Shoulder is the best predictor cut of the lamb carcass composition by bioimpedance.

1. Introduction

Many methods are available for assessing the proximate carcass composition of a variety of livestock; however, the most common approaches for this type of assessment are destructive, time-consuming and utilize noxious chemicals (Zaniboni-Filho *et al.*, 2015). Dissection of small regions of the carcass, while precise and requiring little expenditure for capital equipment, would be slow, labor-intensive and result in reduced carcass marketability/value (Stanford, Jones, & Price, 1998). In the case of lambs, much effort has been done in assessing the composition of specific muscles, especially *longissimus dorsi* muscle, due to its larger size in comparison with other muscles. However, the lamb meat consumption includes also some subcutaneous and intermuscular adipose tissues that, most of the time, are not included in the analysis but contribute to the total fat intake in the diet (Campo *et al.*, 2016). The purchase of sheep meat is commonly performed after splitting the carcass in different joints, which vary from region to region. There are differences in composition among these joins (Kempster, 1981; Owens, Dubeski, & Hansont, 1993). Thus, such information need to be passed on to consumers, whose consider buying a leaner cut according to their preferences.

Among the various alternatives available, bioimpedance is an emerging technology with great potential in food quality control (Pérez-Esteve *et al.*, 2014). Bioimpedance analysis both in vivo (Anderson B. Moro *et al.*, 2019) as on carcass (Silva *et al.*, 2018) showed promising results as a means of predicting carcass composition of lambs in commercial situations, given its precision, simplicity, and portability. The BIA technique has conventionally been used for total body composition by sending an electrical signal from hand-to-foot. This technique has advanced and it can now be used to estimate total and segmental body composition (Kyle *et al.*, 2004; Nickerson, 2018). Segmental bioimpedance analysis (SBIA) offers a simple practical method for assessing the composition of body segments (Ward, 2012). The inspection of the composition of lamb carcass cuts by SBIA is based on the differences of electrical conductivity, mainly, between fat and lean. Lean is a far better conductor of current than fat mass (Berg & Marchello, 1994; Lukaski, Johnson, Bolonchuk, & Lykken, 1985). By introducing a sinusoidal current of 800 µA at 50 kHz to the retail cuts, is expected that the bioelectrical impedance variables being related to the composition of the respective cuts and/or lamb carcasses. Additionally, bioimpedance was not yet used on small cuts to estimate important industrial and nutritional parameters of their own cuts and of lamb carcasses. Then, the objective of this study was to evaluate the potentiality of segmental bioimpedance analysis to predict the edible portion composition of each retail cuts and select the best cut predictor of the lamb carcass composition.

2. Material and Methods

2.1. Animal Management and carcass evaluation

All procedures involving animals were reported by Anderson B. Moro et al. (2019) and were approved by the Ethics Committee on Animal Research of the Federal University of Santa Maria, Brazil. Briefly, thirty-one Texel and Ile de France crossbred ram lambs were used for the purpose of this research. The animals were slaughtered at pre-established slaughter weights of 20, 26, 32, or 38 kg. After the slaughter, carcasses were stored in a chilling chamber at a temperature of 2 ºC. Thereafter, the carcasses were weighed to register cold carcass weight and longitudinally split into two halves. The right half carcasses were weighed and then divided into four retail cuts; leg, rib, shoulder, and neck, as shown in Fig. 1. According to Osório (1998), leg

is the hind limb of the carcass, sectioned at the joint of the last lumbar vertebra and the first sacra and at the middle portion of the tarsus bones. Rib is the part of the carcass sectioned between at the last cervical vertebra and the first thoracic and at the last lumbar and the first sacra. Shoulder is the anterior limb of the carcass, including the musculature of the scapula, and at the distal part. The section is made at the middle portion of the carpal bones. Neck is the portion between its atlanto occipital section and an oblique cut that passes between the seventh cervical and the first dorsal vertebras towards the tip of the sternum and ending at the inferior border of the neck. Each cut was weighed (kg) and its length (cm) were taken from at its extremities, horizontally for neck and rib, and vertically for shoulder and legs. Thereafter, bioimpedance measurements were performed in each retail cut from the lamb carcasses.

2.2 Bioimpedance measurements

A single-frequency BIA equipment (model Quantum II, RJL Systems, Inc., Detroit, USA) was used to make the measurements. A sinusoidal current of 800 µA at 50 kHz was applied to the different tissues and the resulting voltage was measured. Then, resistance and reactance values were calculated. The technique was four-electrode connected to the retail cuts of the carcass by color-coded clips. The black and red electrodes were configured as current and pick-up, respectively. The internal side of each retail cut was laid on plastic tarpaulin for insulation. Stainless steel needles with spiral cable (0.25 x 50 mm) were used as electrodes and inserted in the external side of the cuts following a standard penetration depth. In each retail cut was proposed one electrode placement methodology, as represented in Fig. 2.

The distal current electrodes were inserted onto the extensor muscle complex of shoulder and leg, approximately 3.0 cm proximal to the carpal and tarsal articulations, respectively. The proximal current electrodes were attached at the middle portion of these cuts, 2 cm from their longer extremities. On rib, cranial and caudal current electrodes were inserted 2 cm from its longer extremities at the middle portion on the epaxial muscles. On neck, cranial and caudal current electrodes were positioned at the middle portion, 2 cm from their extremities. The pick-up electrodes were attached in a straight line, 10 cm from the current ones, except on neck, which they were inserted 2 cm from the current electrodes.

The resistance (*Rs*, Ω) and reactance (*Xc*, Ω) valous measured in each retail cut were used to calculate the value of impedance modulus (*Z*, Ω), following the formula proposed by Lukaski *et al.* (1985). Phase angle (PA) was calculated from the relationship between the arch tangent of reactance and resistance, and to convert the radian values into degrees, the PA values were multiplied by 180º/π, according to Lukaski (2013). The bioelectrical volume (*V*, cm^2/Ω) was obtained by calculating the relationship between the respective squared length and resistance; $V = length^2/Rs$ (Jenkins, Leymaster, & Turlington, 1988). Resistive density (*RsD*, kg^2/cm^2 Ω) and reactive density *(XcD*, kg^2/cm^2 Ω) were obtained through the formulas described by Zollinger, Farrow, Lawrence, & Latman (2010), with minor adaptations: $RsD = weight^2/(length^2/Rs)$ and $XcD = weigth^2/(length^2/Xc)$.

2.3. Laboratory analyses

After BIA data were recorded, each cut was deboned in order to obtain the soft tissue weight (edible portion) of each cut. This fraction is composed most of muscles and fat, but also by blood vessels, nerves, and connective tissue. The soft tissue obtained from each cut was ground, homogenized, and submitted to laboratory analyses. Each sample was analyzed in duplicates. Moisture (930.15), protein (992.15), and ash (942.05) were determined according to AOAC (1995) methods. Fat was determined according to the method proposed by Bligh & Dyer (1959). The weight of lean was obtained by the sum of the respective weights of moisture and protein of each cut (Jenkins *et al.*, 1988). Crude energy content (E, MJ) of the soft tissue of each cut was obtained using the caloric equivalents of fat and protein, according to the ARC (1980). The soft tissue, moisture, ash, protein, fat, lean, and crude energy contents of each cut were used to determine the half carcass composition, and then, these values were adjusted to the cold carcass weight.

2.4. Statistical analysis

A descriptive statistical analysis was performed to characterize the database. Multiple regression analyses were performed. The edible components of the retail cuts or lamb cold carcasses were used as the dependent variables and bioimpedance measurements on cuts as the independent ones. Stepwise regression was used to

eliminate the variables that did not influence variation in the models. A. B. Moro et al. (2019) brings a detailed description of the regression analysis applied in this study. The biostatistical models were selected for presenting the highest coefficient of determination (R^2), lowest root mean square error (*RMSE*), and the Mallows Cp statistic (Cp) closest to the number of parameters included in the model. Outliers and systematic bias were identified by plotting studentized residuals against the predicted values and by evaluating Cook's D coefficients.

Predictive performance of the models was assessed using leave-one-out cross-validation. Briefly, from the complete dataset one cut or carcass was selected and regression parameters were estimated with data of the remaining $n - 1$ cut or carcasses. Values of the soft tissue components of each cut or of the cold carcass were predicted for the selected cut or carcass by this regression function, respectively. Predicted and observed values were compared using the Model Evaluation System (MES v.3.1.13, http://nutritionmodels.com/mes.html) to measure precision and accuracy of the models (Tedeschi, 2006) by assessing the highest coefficient of determination (R^2), lowest root mean squared error of prediction (*RMSEP*), and the concordance correlation coefficient (*CCC*) closest to 1. Data were considered statistically significant when $P < 0.05$ for all the statistical analyses performed. Minitab software (v.17.1.0, Minitab Inc., State College, PA, USA) was used for this purpose.

3. Results

3.1. Descriptive statistic

The descriptive statistic of SBIA measurements are shown in Table 1. The means of *Rs* from the highest to lowest values were 344.7, 276.5, 241.7, and 203.7 Ω, for neck, rib, shoulder, and leg, respectively. In turn, for *Xc* from the highest to lowest means were 60.19, 59.55, 50.13, and 42.77 Ω, for rib, neck, leg, and shoulder, respectively. An outstanding was to the *Xc* on neck, which showed much higher variation than on other cuts. Among all independent variables, *XcD* was the one that had highest variation, followed by *RsD* in all cuts. The descriptive statistic of retail cuts and lamb carcass parameters are shown in Table 2. The weight of the cuts ranged from 22.62 to 27.88%, similar to the variability of the cold carcass weight (27.71%). Kilograms of soft tissue, moisture, ash, protein, and lean for all cuts varied from 20.38

to 33.33%. Fat was the variable that had the highest variation in all cuts. Similar behavior happened on cold carcass. The means of crude energy from the highest to lowest were 19.09, 17.10, 10.65, and 3.58 MJ for rib, leg, shoulder, and neck.

3.2. *Prediction models of the retail cuts composition*

The best predictive models for the nutritional parameters analyzed of the edible portion of each retail cut from lamb carcasses by SBIA are presented in Table 3. On Leg, *XcD* accounted for 84.29, 46.30, 79.67, and 83.99% of the soft tissue, ash, fat, and crude energy variance, respectively. Whereas, *RsD* explained alone 81.63, 83.00, and 83.45% of moisture, protein, and lean on leg. When *RsD* was included in the models to predict soft tissue and ash, after *V*, *XcD* stopped contributing to these models and was removed from them. Bioelectrical volume was the second variable included in the predictive models for soft tissue, moisture, ash, protein, and lean, and the third one for energy. In turn, *Xc* was the second variable for predicting fat and energy, and the third one for protein. On rib, *XcD* accounted for 85.82 and 81.49% for soft tissue and moisture variance. Following the stepwise procedure, *V* and *RsD* were added in these models. When *RsD* entered in the model to predict moisture, *XcD* was removed. Otherwise, to predict soft tissue, when *Rs* plus *Z* entered in the model, *RsD* was removed. Reactive density was the only predictive variable for ash and explained 53.30% of its variation on the edible portion of rib. Resistive density accounted for 83.37 to 87.58% in fat, protein, lean, and crude energy content. In these models, *V* was the only another variable that contributed to improve their predictions.

Reactive density was the best predictive variable for all models on shoulder, which explained from 71.91 to 85.90% the variation of the edible portion components of this cut. In turn, *RsD* was the best predictive variable for all models on neck and explained 41.02 to 87.01% the variation of those edible portion compounds of the neck. Bioelectrical volume was the second predictive variable for soft tissue, moisture, protein, lean, and energy on shoulder. Bioelectrical volume, followed by *Rs*, was the second variable for predicting lean and the only another variable for predicting all other parameters on neck. Resistive density was the last variable included in the models to predict moisture, protein, and lean on shoulder. Thereafter, *XcD* was removed from these models. The use of XcD, V, RsD, and Z explained 99.93% of the variation of soft tissue on shoulder. Reactance was the only another best predictive variable for ash

and fat on shoulder and together with *XcD* accounted for 91.00 and 82.59% of their variance on this cuts, respectively. The *PA* was only used to predict the energy of the edible portion of shoulder and improved its prediction in 3.86%. The lowest precision and accuracy among the predictive models of the retail cut compounds were the amount of ash on leg, rib, and neck and fat on shoulder. In turn, the prediction models of soft tissue were the highest accurate among the cuts.

3.3. Prediction models of the lamb carcass composition by SBIA

The final predictive models for the edible components from lamb carcasses though SBIA are shown in Table 4. On leg, *RsD* was the best predictive variable for all nutritional parameters analyzed and accounted for 65.21 to 82.43% of their variation on carcass. Bioelectrical volume was included in all models and improved the prediction in 8.79 to 19.38%. Besides *RsD* and *V*, *Xc* was added in the predictive models for soft tissue, protein, and crude energy content, while for ash and lean was included *XcD*. On rib, *XcD* alone explained 66.57 to 86.47% of the variance for ash, moisture, lean, protein, and soft tissue. In turn, to predict fat and energy *RsD* accounted for 86.40 and 87.24% of its variation on carcass. Similar to SBIA on leg, on rib *V* was also used in all models to predict the carcass components and improved the prediction power in 8.33 to 15.80%. Resistive density yet was used to predict protein and lean, whereas *PA* was used to predict soft tissue.

On shoulder, *XcD* was the best predictive variable for all parameters, ranging from 80.85 to 90.36% of variance, except for ash, which *RsD* accounted for 68.84% of its variation on soft tissue of lamb carcass. Bioelectrical volume was added in all models, except for fat, where *Xc* was the second predictive variable and improved its prediction in 4.46%. Resistive density was the third variable included in the models for predicting soft tissue, moisture, protein, fat, and lean. Except for fat, when *RsD* density entered in those models, *XcD* stopped contributing to its prediction power and was removed from the models. For crude energy, *PA* was added in the model and improved its prediction in 5.00%. The predictive models of the nutritional parameters analyzed on lamb carcasses by SBIA on neck had the same behavior in all models. In those case, *RsD* alone explained 48.57 to 77.15%. Bioelectrical volume was the only another variable used and contributed in 9.75 to 20.92% to the prediction power of those models. Ash and soft tissue were the parameters on carcass that showed, respectively,

the lowest and highest accuracy for SBIA in all carcass cuts. At large, shoulder showed to be the best predictor cut of the edible components of lamb carcasses by SBIA.

4. Discussion

On conventional bioimpedance protocols, the goal is to estimate the whole carcass composition. For that, the measurements are made at the whole body/carcass or usually at dorsal region of them. They consider a homogeneous composition throughout all carcass, which, according to our results (Table 2), is not true. Thus, the use of SBIA is justified because the measurements are made in small cuts in order to assess the composition of each cut of the carcass. Moreover, lamb carcasses from different genders, breeds, or production systems have a broad-ranging variability in quality of the raw meat, manly which concerns appearance, flavor, and its nutrients (Zhao *et al.*, 2017). In such way, it also causes high variation in the commercialized products. Therefore, take the bioimpedance measurements on small cuts or at the most representative of the lamb carcass composition must reduce predicting errors.

Segmental bioimpedance analysis is commonly used in humans to better estimate some physical or chemical component of interest by local assessment or by the sum of that component evaluated in small parts of the body. Limitations of whole body bioimpedance measurement in evaluating body segment compartments have given rise to the demand for segment localized bioimpedance analysis applications (Khalil, Mohktar, & Ibrahim, 2014). The principle of this technique is based on the impedance to the flow of a constant, microampere alternating current passed through cylinders with conductive fluid that represent trunk and limb segments (Kyle *et al.*, 2004). The human body, in this case, is considered as 5 imperfect cylinders (segments); 2 arms, trunk, and 2 legs. In lamb carcasses, is possible to assess the electrical impedance at different ways, such as in whole carcass extension (Cosgrove, King, & Brodie, 1988; Jenkins *et al.*, 1988), at the dorsal site of carcass (Berg & Marchello, 1994; Berg *et al.*, 1997; Silva *et al.*, 2018; Slanger *et al.*, 1994), and over a range of frequencies (Altmann, Pliquett, Suess, & Von Borell, 2004; Hegarty, McPhee, Oddy, Thomas, & Ward, 1998). The use of impedance spectroscopy enables to assess total water and also its intra- and extracellular distribution of the biological material under test (Pliquett, 2010). However, despite the theoretical advantages of using multiple frequencies, there is no apparent or significant advantage from multi-frequency BIA or impedance

spectroscopy compared to a single frequency of 50 kHz, for the same parameters evaluated here.

The differential of our proposed protocols of measurements is that they are collected on the retail cuts after they are separated from the cold carcasses. The prediction of body/carcass composition from impedance data includes many potential sources of error (Ward, 2012). By this protocol, the electrical current is not spread or lost by any connected part of the carcass and, therefore, may better be related to the soft tissue composition of each cut. Another advantage of SBIA is the possibility of evaluate the edible portion of small cuts from the carcass. By this way, it serves as important enhance for the meat industry, mainly which regard to retailers, because a specific cut could be used as raw material for another product with precise information about fat, protein, and/or water composition or simply to make a product with more or less energy.

In humans, SBIA provides indirect prediction of body composition whose accuracy is yet to achieve that of reference techniques such as densitometry, magnetic reference imaging, or dual energy x-ray absorptiometry (Kyle *et al.*, 2004; Nickerson, 2018; Ward, 2012). On lamb carcasses, we referred this technique to the real chemical analyses of each cut and of the whole carcass; therefore, its accuracy must be higher. The placement of the electrodes is of importance in achieving reproducible and accurate results. Some authors reported the best results of the electrode placement on dorsal region on lamb carcasses (Altmann *et al.*, 2004; Berg & Marchello, 1994). However, back fat and the tissue between ribs comprising a high fat content, which it exhibits high impedance (Altmann & Pliquett, 2006). Therefore, the positioning of electrodes in a large extend may improve the accuracy of determining the whole carcass impedance, once, a greater proportion of the carcass is contained between the current and measurement electrodes (Hegarty *et al.*, 1998). The same happen with small cuts because those measurements need to be representative and comparable with the properties associated with the saleable meat.

The main challenge for the use of BIA measurement to determine that composition is to recognize the region and cut that can be utilized to obtain BIA measurements that will best correspond to overall cut or carcass composition (Zaniboni-Filho *et al.*, 2015). On the basis of a pilot study, it was decided that the electrodes should be situated on simple anatomic definition in order to ensure easy access and good contact of electrodes. Segmental bioimpedance data were collected in a manner for practical

application by researcher or industrial on-line personnel. Nonetheless, it can be tested in different cuts from those presented in this paper, according to the commercial interesting of each region.

In the carcass, electrical conduction is via the aqueous phase and will also depend on the ionic distribution within lean tissue and the protein matrix of adipose tissue (Cosgrove *et al.*, 1988). Meat can be represented by an array of highly elongated conducting cells isolated from each other by insulating membranes (Damez, Clerjon, Abouelkaram, & Lepetit, 2008). Cell membranes are composed of a phospholipid bilayer, and at low frequencies is nonconductive (dielectric). Dielectrics do not carry a charge but briefly hold a charge before releasing it. The more dielectric material, the more charges can be held, and the higher the reactance (Hartman, Margraf, Hafs, & Cox, 2015). Theoretically, reactance of the capacitor is a measure of the volume of the cell membrane capacitance and an indirect measure of the intracellular volume or body cell mass (Norman, Stobäus, Pirlich, & Bosy-Westphal, 2012). Resistance is proportional to the voltage of an applied current as it passes through a substance and it measures the conductive characteristics of bodies and fluids. Therefore, resistance increases as the proportions of fat and bone content in tissue increase because fat and bone are poor conductors of electricity; by contrast, resistance decreases as the proportions of water and muscle mass content in tissue increase because water and muscle are good conductors of electricity (Zaniboni-Filho *et al.*, 2015).

Carcass fluid is the total volume of fluids inside a carcass. These fluids contain several ion types with different concentrations, however the main ions in extracellular fluids are Na^+ and Cl^-, and in intracellular fluids are K^+ and PO^{-4} (Khalil *et al.*, 2014). These intra- and extracellular fluids, electrolytes, and minerals act as conductors and comprise a large percentage of the lean tissues in the carcass. Fat is largely present as adipose tissue, which is conductive but much less than lean tissues, and intimately mixed in the lean. In this case, the same amount of lean but with the presence of different amounts of fat have different impedance/resistance due to the geometric change induced by inclusion of the varying amounts of fat in the lean. However, it is clear that bioimpedance is more related to the water composition and ionic solution than properly the fat composition, mainly because of the fat distribution, which is irregular over the carcass and their cuts. Furthermore, impedance variations during the pre-rigor phase were linked to membrane modifications (Damez *et al.*, 2008). In this

case, impedance on cuts is mainly influenced by the total amount of water on each cut and by membrane state (Damez & Clerjon, 2013).

Resistance and reactance measured were used to derive other electrical property equations, and thus, representing different aspects of how current flows through the carcass. The new variables such as resistive and reactive densities indicate promising utilization to serve as an aid to further understanding behavior of the current over biological tissues, mainly those related to meat. Once, much of the predictive power is achieved through the relationship between length and mass (Lukaski *et al.*, 1985). Density of a given material is obtained by its mass per unit of volume. Electrical density was a concept employed by Zollinger *et al.* (2010), which showed that it is composed of two components; resistive density and reactive density. Strong correlations were found between both densities and beef carcass (Zollinger *et al.*, 2010) and lamb carcass parameters, yet assessed in vivo (A. B. Moro *et al.*, 2019; Anderson B. Moro *et al.*, 2019). As it was observed in the evaluation of the edible portion of the cuts and of the carcass, within the bioimpedance variables, resistive and reactive densities, followed by volume, were the ones that most explained the variation of the physical and chemical composition over carcass and on their cuts.

Segmental bioimpedance analysis on shoulder showed higher accuracy to predict the masses of moisture, protein, fat, lean, and crude energy content on carcass than properly at shoulder. Similar behavior happened of SBIA on leg to predict ash, protein, and fat, and on rib for prediction ash, fat, and energy content on carcass. Shoulder showed to be the best representative cut for predicting all parameters assessed on lamb carcasses, except for crude energy, where rib was the best one. In turn, SBIA on neck was the worst representative cut to predict the lamb carcass composition. Some models derived from BIA measurements on lamb carcasses had also great precision. The weight of lean was predicted by BIA on chilled carcass with R^2 of 0.94 (*RMSE* = 0.425, kg) (Jenkins *et al.*, 1988). While, for predicting weight of retail-ready primal cuts from BIA measurement recorded on hot carcasses the R^2 reached 0.91 (*RMSE* = 0.299, kg) and on cold carcasses the R^2 was 0.95 (*RMSE* = 0.237, kg) (Slanger *et al.*, 1994). Berg *et al.* (1997) reported lower coefficients of determination and higher *RMSE* than those aforementioned researchers for total dissected carcass lean weight on warm carcass (R^2 = 0.78, *RMSE* = 0.980, kg) and on chilled carcass (R^2 = 0.81, *RMSE* = 0.892, kg). On warm beef carcasses, fat mass was predicted by electrical conductivity with remarkable precision (R^2 = 0.95) (Slanger & Marchello, 1994).

According to Damez & Clerjon (2013) measurements of fat content after rigor mortis are not consistent, because impedance is also influenced by membrane state. On warm carcasses, no membrane or extracellular compartment modifications occur immediately after slaughter and the temperature is stable. Although these facts are true, we found great accuracy for fat mass in all retail cuts and on carcass, where the R^2 ranged from 0.83 to 0.95. Silva *et al.* (2018) reported similar R^2 (0.86) for grams of fat from muscle on cold carcasses of lambs.

A robust regression equation more effectively predicts the dependent variable in a wide population distribution. Thus, it reduces the effect of outlying observations that otherwise have a strong influence on regression analysis, leaving the residuals of influential observations large, making them more easily identified by the predictive model (Berg & Marchello, 1994). At model selection, many statistic parameters must be considered to select the best predictor model. In our study we considered the higher R^2, smaller RMSE, and the Cp smaller or closest to the number of predictors in the models plus one. By the last parameter, some models were more precise in estimating future responses, with small variance. Thus, the assessment of the adequacy of models is only possible through the combination of several statistical analyses and proper investigation regarding the purposes for which the mathematical model was initially conceptualized and developed for (Tedeschi, 2006). Three main parameters (R^2, *RMSEP*, and *CCC*) were considered on the evaluation of the degree of accuracy of those models. Therefore, high significant linear correlation between actual values and the predicted values, low values of root mean square error of the cross validation prediction, and concordance correlation coefficient closest to 1 showed that the presented models are good enough to predict all the parameters evaluated. Although some models were far better than others, such as for predicting soft tissue and ash on carcass, they had an acceptable accuracy.

Additionally, value-based marketing and/or processing meat products is dependent on accurate measurements of physical and chemical characteristics whose differential pricing and/or processing can be based (Slanger *et al.*, 1994). Development of carcass or retail cuts merit-pricing systems requires the use of objective technology for assessing the edible components and its distribution throughout the carcass (Berg *et al.*, 1997). For that, the SBIA is a simple technology able to accurately predicting the composition of the edible portion from the smaller cuts and lamb carcasses. By this data, the yield of these cuts or carcass components can also be estimated, and hence,

SBIA can be used in this merit-pricing system. Furthermore, the way to keep or even increase sheep meat participation in the overall meat consumption will probably rely on the differentiation and adding value of the product, particularly to those consumers which desire and that are able to pay for such differentiate meat (Montossi *et al.*, 2013). Combined with a greater awareness and higher expectations of product quality by processors, retailers, and consumers, new and complex challenges face the industry in terms of product standardization while maintaining production profitability (Duncan *et al.*, 2007).

The development of rapid, low-cost, non-destructive methods for food quality monitoring has been one of the most interesting research field of food industry in the last few years and it would be an important advance for the industry, governments, and consumers (Pérez-Esteve *et al.*, 2014). The benefits of identification of low quality meat for industry include reducing economic losses and distributing the best destination of carcasses or their cuts (Zhao *et al.*, 2017). Packers would have information with which to more efficient manage their operations and producers would have information for possible negotiation of value-pricing. Moreover, manufacturers would easily assess the quality of every product to monitor processing, and obtain reliable information for customers and further processing manufacturers (Damez & Clerjon, 2013). In such way, bioimpedance technology has advantages of being easily implemented and shows potential to develop on-line detecting instrument to replace traditional methods to realize time, cost, skilled persons saving and further quality grading (Zhao *et al.*, 2017). Therefore, the SBIA method showed great perspective of being used regularly to determine important physical and chemical parameters of the edible portion of lamb carcasses or smaller cuts.

5. Conclusion

Segmental bioimpedance analysis is a promising and innovative technique that might be used easily in practice and serve to evaluate the composition of small cuts and/or lamb carcasses. Shoulder is the best retail cut, most representative, and accurate for predicting physical and chemical components of the edible portion of lamb carcasses by SBIA.

Declarations of interest

All authors have none conflict of interest to declare.

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Table 1 Descriptive statistics of segmental bioimpedance analysis (SBIA) on the retail cuts of the lamb carcasses.

	n	Min	Max	Mean	*SD*
SBIA parameters on leg					
Resistance, Ω	31	152.0	333.0	203.7	35.71
Reactance, Ω	31	22.00	69.00	50.13	9.140
Impedance, Ω	31	160.0	336.7	210.0	35.27
Phase angle, º	31	6.340	18.21	14.06	2.882
Bioelectric volume, cm^2/Ω	31	6.590	13.960	10.36	1.946
Resistive density, kg^2/cm^2 Ω	31	0.179	0.738	0.442	0.153
Reactive density, kg^2/cm^2 Ω	31	0.030	0.214	0.114	0.050
SBIA parameters on rib					
Resistance, Ω	31	180.0	436.0	276.5	60.00
Reactance, Ω	31	34.00	93.00	60.19	14.54
Impedance, Ω	31	183.2	439.0	283.2	60.30
Phase angle, º	31	6.670	17.79	12.45	2.633
Bioelectric volume, cm^2/Ω	31	3.230	8.540	5.577	1.235
Resistive density, kg^2/cm^2 Ω	31	0.332	1.851	0.807	0.378
Reactive density, kg^2/cm^2 Ω	31	0.052	0.392	0.185	0.098
SBIA parameters on shoulder					
Resistance, Ω	31	174.0	483.0	241.7	54.29
Reactance, Ω	31	18.00	61.00	42.77	11.12
Impedance, Ω	31	177.9	486.0	245.7	54.28
Phase angle, º	31	3.680	13.39	10.20	2.514
Bioelectric volume, cm^2/Ω	31	3.070	8.330	6.522	1.267
Resistive density, kg^2/cm^2 Ω	31	0.113	0.499	0.265	0.094
Reactive density, kg^2/cm^2 Ω	31	0.010	0.112	0.050	0.026
SBIA parameters on neck					
Resistance, Ω	31	132.0	539.0	344.7	88.70
Reactance, Ω	31	19.00	191.0	59.55	30.23
Impedance, Ω	31	133.4	542.7	350.5	91.20
Phase angle, º	31	3.700	21.58	9.733	3.272
Bioelectric volume, cm^2/Ω	31	0.390	1.890	0.971	0.260
Resistive density, kg^2/cm^2 Ω	31	0.079	0.439	0.215	0.099
Reactive density, kg^2/cm^2 Ω	31	0.009	0.080	0.037	0.019

n = Sample size; Min = Minimum; Max = Maximum; *SD* = Standard deviation.

Table 2 Descriptive statistics of the composition of the edible portion of retail cuts and cold carcasses of lambs.

	n	Min	Max	Mean	*SD*
Leg parameters					
Weight, kg	31	1.110	3.085	2.109	0.477
Length, cm	31	38.50	49.00	45.31	2.825
Bone, kg	31	0.226	0.508	0.399	0.067
Soft tissue, kg	31	0.884	2.577	1.729	0.411
Moisture, kg	31	0.611	1.465	1.109	0.226
Ash, kg	31	0.009	0.024	0.015	0.004
Protein, kg	31	0.187	0.479	0.328	0.078
Fat, kg	31	0.077	0.476	0.241	0.102
Lean, kg	31	0.798	1.928	1.434	0.297
Crude energy, MJ	31	7.440	28.44	17.10	5.630
Rib parameters					
Weight, kg	31	1.090	3.020	2.073	0.578
Length, cm	31	32.00	45.00	38.55	3.765
Bone, kg	31	0.217	0.525	0.373	0.077
Soft tissue, kg	31	0.873	2.563	1.680	0.503
Moisture, kg	31	0.606	1.470	1.064	0.253
Ash, kg	31	0.009	0.022	0.014	0.003
Protein, kg	31	0.162	0.461	0.306	0.087
Fat, kg	31	0.086	0.610	0.283	0.162
Lean, kg	31	0.768	1.931	1.357	0.334
Crude energy, MJ	31	7.280	41.19	19.09	9.200
Shoulder parameters					
Weight, kg	31	0.690	1.875	1.297	0.312
Length, cm	31	33.00	45.00	39.00	2.736
Bone, kg	31	0.133	0.289	0.231	0.041
Soft tissue, kg	31	0.557	1.474	1.048	0.253
Moisture, kg	31	0.400	1.025	0.703	0.152
Ash, kg	31	0.006	0.016	0.010	0.003
Protein, kg	31	0.094	0.299	0.205	0.053
Fat, kg	31	0.046	0.384	0.149	0.087
Lean, kg	31	0.494	1.309	0.908	0.203
Crude energy, MJ	31	4.460	22.04	10.65	4.424
Neck parameters					
Weight, kg	31	0.175	0.690	0.445	0.122

Length, cm	31	13.00	21.00	17.76	1.852
Bone, kg	31	0.044	0.131	0.091	0.023
Soft tissue, kg	31	0.131	0.565	0.348	0.107
Moisture, kg	31	0.094	0.347	0.231	0.058
Ash, kg	31	0.001	0.005	0.003	0.001
Protein, kg	31	0.028	0.103	0.065	0.019
Fat, kg	31	0.008	0.119	0.052	0.030
Lean, kg	31	0.122	0.450	0.293	0.075
Crude energy, MJ	31	0.980	6.760	3.581	1.582
Cold carcass parameters					
Weight, kg	31	6.360	17.36	11.90	2.940
Length, cm	31	47.50	60.00	53.89	3.247
Bone, kg	31	1.288	2.777	2.195	0.393
Soft tissue, kg	31	5.072	14.60	9.706	2.577
Moisture, kg	31	3.551	8.591	6.155	1.328
Ash, kg	31	0.052	0.128	0.087	0.019
Protein, kg	31	0.976	2.645	1.832	0.467
Fat, kg	31	0.493	2.496	1.348	0.607
Lean, kg	31	4.527	11.09	7.938	1.765
Crude energy, MJ	31	42.42	157.6	96.69	34.99

n = Sample size; Min = Minimum; Max = Maximum; *SD* = Standard deviation

Table 3 Biostatistical models for predicting the composition of the edible portion of retail cuts of lamb carcasses through segmental bioimpedance analysis (SBIA).

	Models	Calibration				Cross-validation		
		R^2	*RMSE*	*Cp*	*P*-value	R^2	*RMSEP*	*CCC*
SBIA on leg								
Soft tissue, kg	$Y = -0.1471 + 0.09474V + 2.0036RsD$	0.992	0.038	10.7	< 0.0001	0.990	0.040	0.995
Moisture, kg	$Y = 0.0477 + 1.1687RsD + 0.0546V$	0.970	0.040	4.06	< 0.0001	0.962	0.043	0.981
Ash, kg	$Y = 0.00061 + 0.000937V + 0.01162RsD$	0.681	0.002	0.10	< 0.0001	0.602	0.002	0.763
Protein, kg	$Y = 0.0371 + 0.4191RsD + 0.01372V - 0.00072Xc$	0.943	0.020	2.37	< 0.0001	0.923	0.021	0.961
Fat, kg	$Y = 0.1501 + 2.2910XcD - 0.003256Xc$	0.860	0.040	2.83	< 0.0001	0.815	0.043	0.901
Lean, kg	$Y = 0.0422 + 1.5690RsD + 0.0700V$	0.981	0.042	3.22	< 0.0001	0.976	0.045	0.988
Crude energy, MJ	$Y = 2.2800 + 65.100XcD - 0.1122Xc + 0.6150V + 16.010RsD$	0.944	1.438	3.15	< 0.0001	0.917	1.600	0.957
SBIA on rib								
Soft tissue, kg	$Y = -0.2930 + 4.7960XcD + 0.1811V + 0.0441Rs - 0.0426Z$	0.989	0.057	8.02	< 0.0001	0.968	0.092	0.983
Moisture, kg	$Y = 0.1557 + 0.0834V + 0.5700RsD$	0.957	0.054	2.99	< 0.0001	0.942	0.060	0.971
Ash, kg	$Y = 0.00991 + 0.02297XcD$	0.533	0.002	1.98	< 0.0001	0.451	0.002	0.640
Protein, kg	$Y = -0.0118 + 0.2164RsD + 0.0279V$	0.979	0.013	4.10	< 0.0001	0.972	0.014	0.986
Fat, kg	$Y = -0.2823 + 0.4055RsD + 0.0469V$	0.924	0.047	3.13	< 0.0001	0.905	0.049	0.951
Lean, kg	$Y = 0.1572 + 0.8470RsD + 0.1015V$	0.973	0.057	2.67	< 0.0001	0.966	0.061	0.983
Crude energy, MJ	$Y = -11.260 + 21.750RsD + 2.3960V$	0.966	1.757	0.33	< 0.0001	0.958	1.851	0.979
SBIA on shoulder								
Soft tissue, kg	$Y = 0.0101 + 0.7710XcD + 0.0871V + 1.9221RsD - 0.0002Z$	0.999	0.007	2.85	< 0.0001	0.999	0.008	0.999
Moisture, kg	$Y = 0.0285 + 0.0632V + 0.9921RsD$	0.933	0.041	9.88	< 0.0001	0.912	0.045	0.954
Ash, kg	$Y = 0.0076 + 0.1256XcD - 0.0001Xc$	0.910	0.001	5.58	< 0.0001	0.888	0.001	0.941
Protein, kg	$Y = -0.0199 + 0.0182V + 0.4012RsD$	0.962	0.011	10.5	< 0.0001	0.952	0.011	0.975
Fat, kg	$Y = 0.0696 + 3.7530XcD - 0.0025Xc$	0.826	0.038	8.44	< 0.0001	0.785	0.040	0.881
Lean, kg	$Y = 0.0086 + 0.0813V + 1.3933RsD$	0.952	0.046	13.8	< 0.0001	0.937	0.050	0.968

Crude energy, MJ	$Y = 1.8700 + 186.90XcD + 0.9690V - 0.6840PA$	0.904	1.443	2.94	< 0.0001	0.871	1.561	0.932
SBIA on neck								
Soft tissue, kg	$Y = - 0.0196 + 0.8682RsD + 0.1913V$	0.992	0.010	12.8	< 0.0001	0.990	0.011	0.995
Moisture, kg	$Y = 0.0289 + 0.4633RsD + 0.1050V$	0.961	0.012	2.89	< 0.0001	0.944	0.013	0.972
Ash, kg	$Y = - 0.000013+ 0.0056RsD + 0.0021V$	0.703	0.001	3.09	< 0.0001	0.595	0.001	0.767
Protein, kg	$Y = 0.0022 + 0.1648RsD + 0.0291V$	0.947	0.004	10.5	< 0.0001	0.929	0.005	0.964
Fat, kg	$Y = - 0.0327 + 0.2594RsD + 0.0304V$	0.910	0.009	0.90	< 0.0001	0.889	0.010	0.942
Lean, kg	$Y = 0.0778 + 0.6704RsD + 0.1088V – 0.00009Rs$	0.974	0.013	6.79	< 0.0001	0.960	0.015	0.980
Crude energy, MJ	$Y = - 1.1970 + 13.700RsD + 1.9070V$	0.955	0.350	0.67	< 0.0001	0.946	0.363	0.972

R^2 = Coefficient of determination; *RMSE* = Root mean squared error; *Cp* = Mallows Cp statistic; *RMSEP* = Root mean squared error of prediction; *CCC* = Concordance correlation coefficient.

XcD = Reactive density; *V* = Bioelectrical volume; *RsD* = Resistive density; *Z* = Impedance; *Xc* = Reactance; *PA* = Phase angle; *Rs* = Resistance.

Table 4 Biostatistical models for predicting the composition of the edible portion of lamb carcasses through segmental bioimpedance analysis (SBIA).

	Models	Calibration				Cross-validation		
		R^2	*RMSE*	*Cp*	*P*-value	R^2	*RMSEP*	*CCC*
SBIA on leg								
Soft tissue, kg	Y = - 0.3850 + 12.940*RsD* + 0.5385*V* - 0.0229*Xc*	0.968	0.480	7.20	< 0.0001	0.955	0.526	0.977
Moisture, kg	Y = 0.2680 + 5.8060*RsD* + 0.3348*V*	0.944	0.324	23.4	< 0.0001	0.929	0.345	0.964
Ash, kg	Y = - 0.0028 + 0.1338*RsD* + 0.0051*V* - 0.1946*XcD*	0.850	0.008	0.69	< 0.0001	0.787	0.008	0.884
Protein, kg	Y = 0.0960 + 2.5140*RsD* + 0.0884*V* - 0.0058*Xc*	0.959	0.099	1.69	< 0.0001	0.944	0.109	0.971
Fat, kg	Y = - 1.2820 + 3.4130*RsD* + 0.1193*V*	0.867	0.240	2.20	< 0.0001	0.827	0.261	0.907
Lean, kg	Y = - 0.4090 + 10.250*RsD* + 0.4757*V* - 7.9100*XcD*	0.958	0.382	17.9	< 0.0001	0.940	0.428	0.969
Crude energy, MJ	Y = - 35.500 + 200.70*RsD* + 6.7700*V* - 0.4500*Xc*	0.922	10.32	1.56	< 0.0001	0.892	11.31	0.944
SBIA on rib								
Soft tissue, kg	Y = 3.4010 + 25.470*XcD* + 0.7909*V* - 0.2198*PA*	0.975	0.433	1.14	< 0.0001	0.965	0.477	0.982
Moisture, kg	Y = 1.8210 + 9.8430*XcD* + 0.4696*V*	0.926	0.379	0.83	< 0.0001	0.910	0.399	0.953
Ash, kg	Y = 0.0326 + 0.1273*XcD* + 0.0056*V*	0.781	0.009	1.22	< 0.0001	0.720	0.010	0.844
Protein, kg	Y = 0.2198 + 1.5910*XcD* + 0.1573*V*+ 0.5470*RsD*	0.957	0.102	1.25	< 0.0001	0.941	0.112	0.970
Fat, kg	Y = - 0.9520 + 1.8880*RsD* + 0.1736*V*	0.938	0.193	3.47	< 0.0001	0.912	0.219	0.953
Lean, kg	Y = 1.8370 + 8.8300*XcD* + 0.6506*V* + 1.2300*RsD*	0.942	0.459	1.37	< 0.0001	0.854	0.719	0.921
Crude energy, MJ	Y = - 32.240 + 96.250*RsD* + 10.610*V*	0.976	6.418	3.83	< 0.0001	0.969	6.771	0.984
SBIA on shouder								
Soft tissue, kg	Y = - 1.4750 + 0.9320*V* + 19.295*RsD*	0.982	0.359	3.04	< 0.0001	0.979	0.371	0.989
Moisture, kg	Y = 0.1050 + 0.5088*V* + 10.974*RsD*	0.975	0.218	1.80	< 0.0001	0.970	0.228	0.985
Ash, kg	Y = 0.0120 + 0.1255*RsD* + 0.0065*V*	0.850	0.007	4.80	< 0.0001	0.813	0.008	0.899
Protein, kg	Y = - 0.1832 + 0.1695*V* + 3.4420*RsD*	0.964	0.092	4.00	< 0.0001	0.956	0.097	0.978
Fat, kg	Y = 0.4630 + 30.140*XcD* - 0.0229*Xc* + 2.2700*RsD*	0.954	0.197	4.04	< 0.0001	0.938	0.213	0.968
Lean, kg	Y = - 0.0950 + 0.6738*V* + 14.619*RsD*	0.976	0.286	2.55	< 0.0001	0.970	0.300	0.985

Crude energy, MJ	Y = 4.8000 + 1789.0*XcD* + 13.000*V* – 7.5000*PA*	0.948	10.25	0.48	< 0.0001	0.931	11.07	0.964
SBIA on neck								
Soft tissue, kg	Y = 1.2820 + 3.4130*RsD* + 0.1193*V*	0.896	0.825	1.35	< 0.0001	0.873	0.865	0.934
Moisture, kg	Y = 1.9450 + 20.140*RsD* + 3.3110*V*	0.829	0.577	0.60	< 0.0001	0.788	0.615	0.885
Ash, kg	Y = 0.0199 + 0.1106*RsD* + 0.0453*V*	0.695	0.011	3.31	< 0.0001	0.615	0.012	0.774
Protein, kg	Y = 0.4460 + 3.7020*RsD* + 0.56903*V*	0.882	0.161	1.84	< 0.0001	0.850	0.172	0.921
Fat, kg	Y = - 0.4280 + 5.1570*RsD* + 0.7340*V*	0.828	0.271	0.62	< 0.0001	0.795	0.280	0.889
Lean, kg	Y = 2.2590 + 14.270*RsD* + 2.7750*V*	0.866	0.692	0.10	< 0.0001	0.829	0.745	0.909
Crude energy, MJ	Y = - 6.2000 + 289.00*RsD* + 42.360*V*	0.862	13.42	1.20	< 0.0001	0.835	13.87	0.912

R^2 = Coefficient of determination; *RMSE* = Root mean squared error; *Cp* = Mallows Cp statistic; *RMSEP* = Root mean squared error of prediction; *CCC* = Concordance correlation coefficient.

V = Bioelectrical volume; *RsD* = Resistive density; *XcD* = Reactive density; *Xc* = Reactance; *PA* = Phase angle.

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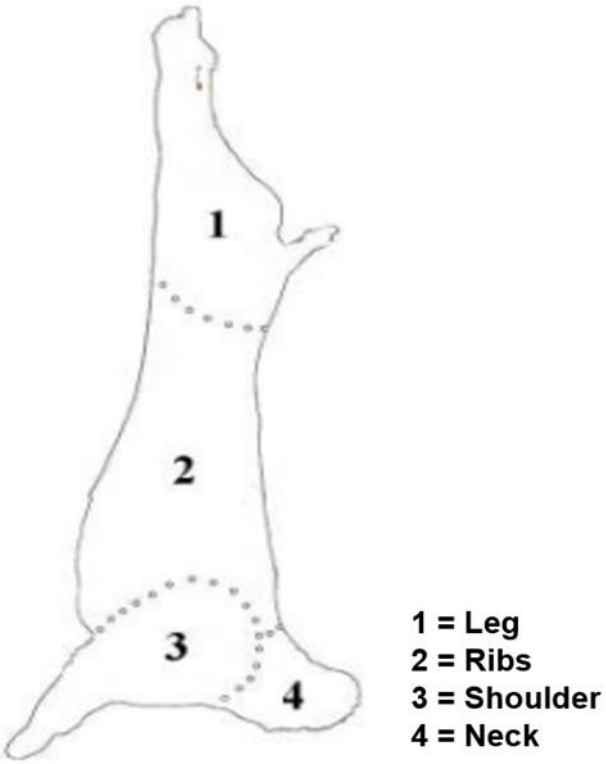
Figure 1: Retail cuts of lamb carcasses.



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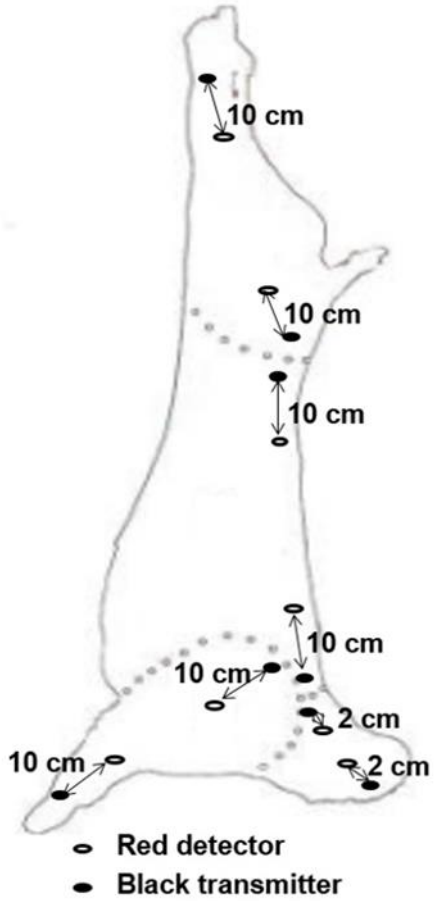

4 ARTIGO 3 - BIOIMPEDANCE ANALYSIS REPLACING TRADITIONAL METHODS FOR PREDICTING LAMB COMPOSITION[3]

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Bioimpedance analysis replacing traditional methods for predicting lamb composition

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Abstract

This study aimed to replace tradition methods of assessing lamb composition by bioimpedance analysis (BIA) and use *longissimus dorsi* muscle as representative of

the carcass composition. Thirty-one lamb carcasses were assessed and a BIA equipment used to measure resistance and reactance at *longissimus dorsi* muscle. Some accessory variables for predicting lamb composition, such as resistive and reactive densities were tested. Multiple regression analyses were carried out using lamb components as dependent variables and BIA measurements as independent ones. Reactive and/or resistive densities explained the most variation of all parameters evaluated. Biostatistical models accounted for 68% to 99% of the variation in weights of moisture, ash, protein, fat, lean, and crude energy at *longissimus dorsi* muscle and from 83% to 92% in soft tissue, moisture, ash, protein, fat, lean, and crude energy in the edible portion of the carcasses. Bioimpedance performed on *longissimus dorsi* muscle showed to be a promising technology to replace expensive traditional methods for evaluating lamb composition.

Keywords: impedance, lamb meat, meat composition, meat quality, meat technology, resistive density

Highlights

- Bioimpedance is able to replace traditional methods of assessing meat composition.
- Lamb composition is accurately predicted though bioimpedance analysis.
- *Longissimus dorsi* muscle is indicate to estimate the lamb carcass parameters by bioimpedance.

1. Introduction

Traditional methods for quality assessments of lamb, such as dissection followed by chemical analyses, are destructive, time-consuming, complicated for experiments,

and requiring skilled operators (Zhao *et al.*, 2017). Dissection of small regions of the carcass, while precise and requiring little expenditure for capital equipment, is slow, labor-intensive and result in reduced carcass marketability/value (Stanford, Jones, & Price, 1998). The current trend in monitoring meat quality is to move the measurements of quality from the laboratories to the processing lines. Sophisticate techniques and new methodologies based on different principles, procedures, and/or instruments are required for measuring different meat quality attributes. To satisfy the increased awareness, sophistication, and greater expectation of consumers, it is necessary to improve automated quality inspection (Valous, Zheng, Sun, & Tan, 2016).

The ideal method for measuring lamb composition should be relatively inexpensive, require little inconvenience for the individual, be operated by unskilled technicians and yield highly reproducible and accurate results. Among the available techniques, few methods meet these requirements, one being bioimpedance analysis (BIA) (Ward, 2012). A prediction of muscle composition is possible by using the passive electrical properties (Altmann & Pliquett, 2006). Bioimpedance has been proved as an emerging detection technology with advantages of being fast, nondestructive, inexpensive, and easily implemented and shows potential to replace traditional methods in order to save time, cost, and skilled persons (Moro *et al.*, 2019; Silva *et al.*, 2018; Zhao *et al.*, 2017). A sinusoidal current of 800 µA at 50 kHz is introduced into the material under test via transmitter terminals and received by detector terminals (Pliquett, 2010). Impedance is low in lean tissue where intracellular fluid and electrolytes are primarily contained, but high in fat tissue. Using BIA, the meat composition is estimated by measuring the impedance (resistance and reactance) of a current through a material under test and then regressing (calibrating) these measures with actual composition numbers for that material (Hartman, Margraf, Hafs, & Cox, 2015).

In the case of lambs, much effort has been done in assessing the composition of specific muscles, especially *longissimus dorsi* muscle, due to its larger size in comparison with other muscles. At the best of our knowledge, no research endeavors are yet executed using accessory BIA variables, such as resistive and reactive densities, at *longissimus dorsi* muscle to predict its chemical composition and the edible components of lamb carcasses. Thus, it is hypothesized that accessory BIA variables used in this specific muscle will be able to predict lamb parameters, once it may be representative of the edible portion of the carcass. Moreover, the electrical current conduction in the muscle is dependent on its composition and thus, it may be an indicative of the lamb carcass composition. Therefore, this study aimed to replace tradition methods used to assess the lamb composition by bioimpedance analysis and use the *longissimus dorsi* muscle as indicate of the lamb carcass composition.

2. Material and methods

2.1. Animal management and carcass handling

All procedures involving animals were reported by Anderson B. Moro et al. (2019) and were approved by the Ethics Committee on Animal Research of the Federal University of Santa Maria, Brazil. The research was conducted at the sheep facility of the Department of Animal Science. In summary, thirty-one Texel and Ile de France crossbred ram lambs were used for the purpose of this research. The animals were slaughtered at pre-established slaughter weights of 20, 26, 32, or 38 kg. After the slaughter, carcasses were stored in a chilling chamber at a temperature of 2 ºC. Thereafter, the carcasses were weighed to register cold carcass weight and longitudinally split into two halves. The right half carcasses were weighed and divided into four retail cuts; leg, rib, shoulder, and neck, according to Osório (1998). Rib is the

part of the carcass sectioned between at the last cervical vertebra and the first thoracic and at the last lumbar and the first sacra. From this cut, *longissimus dorsi* muscle was removed and trimmed. After soon, its weight and length were recorded, and bioimpedance analysis was performed.

2.2. Bioimpedance measurements

A single-frequency BIA equipment (model Quantum II, RJL Systems, Inc., Detroit, USA) was used to make the measurements. A sinusoidal current of 800 µA at 50 kHz was applied to the different tissues and the resulting voltage was measured. Then resistance and reactance values were calculated. The technique was four-electrode connected to the *longissumus dorsi* muscle by color-coded clips. The black and red electrodes were configured as current and pick-up, respectively. The inferior side of each muscle was laid on plastic tarpaulin for insulation. Stainless steel needles with spiral cable (0.25 x 50 mm) were used as electrodes and inserted in the superior side of the muscle following a standard penetration depth. The current electrodes were attached at the middle portion of the *longissimus dorsi* muscle, 2 centimeters from its extremities. The pick-up electrodes were inserted in a straight line, 10 cm from the current ones.

Based on resistance (Rs, Ω) and reactance (Xc, Ω) values measured at *longissimus dorsi* muscle, values of impedance modulus (Z, Ω) were calculated using the formula described by Lukaski, Johnson, Bolonchuk, & Lykken (1985). Phase angle (PA) was calculated from the relationship between the arch tangent of reactance and resistance and to convert the radian values into degrees, the PA value wasere multiplied by $180^{o}/\pi$ (Lukaski, 2013). The bioelectrical volume (V, cm^2/Ω) was calculated as the relationship between squared length and resistance (Jenkins,

Leymaster, & Turlington, 1988). Resistive density (RsD, kg^2/cm^2 Ω) and reactive density (XcD, kg^2/cm^2 Ω) were obtained through minor adaptations of the formulas proposed by Zollinger, Farrow, Lawrence, & Latman (2010).

2.3. Laboratory analyses

After the BIA data were performed, the *longissimus dorsi* muscle was ground, homogenized, and a sample was taken for later chemical analysis. Bones were removed from all cuts in order to determine the soft tissue mass (edible portion) of the half carcasses. The soft tissue obtained from each cut was minced, homogenized, and four samples from each carcass of 200 g were taken for laboratory analyses. The soft tissue of the cold carcass was obtained by the sum of the soft tissue of each cut and adjusted for the cold carcass weight. Moisture (930.15), protein (992.15), and ash (942.05) were chemically determined according to AOAC (1995) methods. Fat was determined according to the method proposed by Bligh & Dyer (1959). All chemical analyses were carried on duplicates. Lean content was calculated as the sum of protein and moisture contents determined (Jenkins *et al.*, 1988). Crude energy content (E, MJ) was obtained using the caloric equivalents of fat and protein according to the ARC (1980). The moisture, ash, protein, fat, lean, and crude energy contents of each cut were used to determine the half carcass composition, and then values were adjusted to the cold carcass weight.

2.4. Statistical analysis

Minitab software (v.17.1.0, Minitab Inc., State College, PA, USA) was used for this purpose. Data were considered statistically significant when $P < 0.05$ for all the statistical analyses performed. A descriptive statistical analysis was performed to

characterize the database. Correlation coefficients between the BIA measurements and lamb components on *longissimus dorsi* muscle and lamb cold carcasses were determined. For the multiple regression analyses, moisture, ash, protein, fat, lean, and energy from the *longissimus dorsi* muscle or soft tissue, moisture, ash, protein, fat, lean, and energy from the edible portion of the carcasses were the dependent variables and bioimpedance measurements the independent ones. Stepwise regression was used to eliminate the variables that did not influence variation in the model. Those variables that did not significantly contribute to the model ($P > 0.05$) were eliminated. The biostatistical models were selected for presenting the highest coefficient of determination (R^2), lowest root mean square error (RMSE), and the Mallows Cp statistic (Cp) closest to the number of parameters included in the model. Outliers and systematic bias were identified by plotting studentized residuals against the predicted values and by evaluating Cook's D coefficients. Data points with a studentized residual outside the range ± 2.5 were considered to be outliers.

Predictive performance of the models was assessed using leave-one-out cross-validation. Briefly, from the complete dataset one sample unit was selected and regression parameters were estimated with data of the remaining $n - 1$ experimental units. Values of the meat components from *longissimus dorsi* muscle or of the carcass were predicted for the selected sample unit by this regression function. Predicted and observed values were compared using the Model Evaluation System (MES v.3.1.13, http://nutritionmodels.com/mes.html) to measure precision and accuracy of the models by assessing the highest coefficient of determination (R^2), lowest root mean squared error of prediction (RMSEP), and the concordance correlation coefficient (CCC) closest to 1, according to Tedeschi (2006).

3. Results

3.1. Descriptive statistic of BIA parameters and of lamb composition

The descriptive statistics of the BIA measurements and lamb composition of the *longissimus dorsi* muscle and of the edible portion of lamb carcasses is shown in Table 1. Resistance and reactance ranged from 459 to 1236 Ω and from 126 to 479 Ω, respectively. The weight and length of the *longissimus dorsi* muscle ranged from 0.150 to 0.500 kg and from 31.0 to 46 cm, respectively. Moisture, ash, protein, and lean had similar variation in the *longissimus dorsi* muscle and quite higher variation than on carcasses. Fat and crude energy both on *longissimus dorsi* muscle and on carcass had similar variation. Nonetheless, fat was the chemical component that showed the highest variation on *longissimus dorsi* muscle as well as on carcass. While, the soft tissue of the carcass had 9.528 kg of difference between the lightest and heaviest carcass.

3.2. Correlations between BIA parameters and lamb composition

Results of the correlation analysis between BIA measurements and *longissimus dorsi* composition and with the edible components of lamb carcasses are presented in Table 2. In one hand, Rs and Z were not correlated ($P > 0.05$) to any parameters of lamb, neither on *longissimus dorsi* muscle nor on edible components of carcasses. In another hand, Xc was not correlated ($P > 0.05$) only to ash content on carcass. These correlations ranged from r = 0.39 to r = 0.55. Similar behavior was found for PA and V to all parameters evaluated, which the coefficient of correlation ranged from r = 0.44 to r = 0.72. However, the highest correlations were found among XcD and RsD with all physical, chemical, and nutrition parameters assessed, both on *longissimus dorsi*

muscle as on edible portion of the carcasses. These coefficients of correlation ranged from 0.71 to 0.95.

3.3. Prediction models of lamb composition

Biostatistical models to predict lamb composition of *longissimus dorsi* muscle and the edible portion of carcasses from BIA variables are shown in Table 3. At *longissimus dorsi* muscle composition, XcD explained the most variation of all parameters assessed. For moisture, protein, lean mass, and energy it accounted from 87.47 to 88.99% of their variation. The V was the second variable included in these models and improved them from 4.66 to 5.11%. In the sequence, RsD was added in these models and improved their prediction power from 3.07 to 4.05%. When RsD entered in these models, XcD stopped contributing to the models and it was removed from them. After that, Z was yet included in these models and the R^2 stayed between 96.63 to 99.13%.

Similar behavior happened in the models to predict moisture, protein, lean mass, energy, and soft tissue at the edible portion of carcasses. Differently, Z was not used in these models. When RsD entered in the models, XcD was removed from them, and it was the last step performed. Although ash on *longissimus dorsi* was most explained by XcD (R^2 = 77.41), followed by V (R^2 = 83.87) and for PA (R^2 = 88.34), on edible portion of carcass it was most explained by RsD (R^2 = 55.47), followed by V (R^2 = 69.51), XcD (R^2 = 78.20), and PA (R^2 = 82.78). Reactive density accounted for 67.57 and 80.58% of the variation of fat on *longissimus dorsi* muscle and on edible portion of carcass, respectively. In addition, to predict fat on the edible portion of carcass, V was also included in that model. At *longissimus dorsi* muscle, the prediction models that showed the highest and poorest precision and accuracy were lean mass and fat,

respectively. In turn, soft tissue and ash had the highest and poorest adequacy among the predictive models on the edible portion of lamb carcasses, respectively.

4. Discussion

Our purposed methodology involves the extraction of the *longissimus dorsi* muscle from cold carcasses. From the point of view of applicability, although this procedure seems to be more applicable in research centers than industry, it is rapid and easy to be performed. According to Duncan *et al.* (2007), because BIA is relatively inexpensive, the equipment portable, and results comparatively easy to generate and understand, the method clearly offers high potential in both commercial and research applications. A method and apparatus for measuring the lamb composition comprises means for maintaining the electrodes in a fixed spatial relation and in good electrical contact with the tissue on which measurements are to be made. Needle electrodes were used in tetrapolar arrangement, where the supply conductors of drive circuits are separated from the measuring one. This is a principle of measurement that helps to eliminate the polarization effect and electrode contact resistance, thus enabling to perform measurements within the potential linear course (Lukaski *et al.*, 1985). To ensure consistency of the measurement, we recommend the electrodes placement in the muscle approximately 2.0 cm distal to its extremities. This procedure seemingly ensures the measurement of impedance throughout the length of the muscle, and therefore, most representative of the edible portion of carcass.

Muscle, and thus meat, has a strongly anisotropic structure organized with elements of various dimensions. For that, impedance varies according to whether current is propagated along or across muscle fibers (Damez, Clerjon, Abouelkaram, & Lepetit, 2008). According to Altmann & Pliquett (2006), different orientation of muscle

fibers with respect to the direction of insertion may explain differences between measurements made at the same time post-mortem and structural differences explain the impedance differences among species. Despite the fact that the BIA to be useful to predict body composition in cattle that have an unusually wide weight range, it is not in cattle that have a narrow weight range (Thomson, Thomas, Ward, & Sillence, 1997). In our study, BIA was tested in a wide range of slaughter weight to have variation on lamb carcass composition. Additionally, breed specific regression equations could improve the accuracy (Altmann & Pliquett, 2006).

Resistance and reactance were used in calculations involving common electrical property equations to generate data that employed in a regression model with proximate composition measures. These derived electrical equations, such as phase angle, volume, and resistive and reactive densities, showed to better represent different aspects of how current flows through the muscle than properly Rs an Xc alone. This can be explained because the electrical impedance of a geometrical system depends on conductor length and configuration, signal frequency, and conductor cross-sectional area (Hartman, Phelan, & Rosendale, 2011). Hence, it is extremely important to consider the relation of Rs and Xc to length and weight of the material under test, once they are narrowly linked to its composition. The high correlations found between these variables and lamb components confirm this sentence. Similar results were found by Berg & Marchello (1994), once they reported that individual BIA variables had relatively low correlations to the various measurements of lean content. However, the combination of BIA variables and weight resulted in an improved estimation of carcass composition.

Bioimpedance calibration models need to be validate to ensure reproducibility and transferability (Hartman *et al.*, 2015). By analyzing the set of the statistical parameters

(R^2, RMSEP, and CCC), the predictive models, both on the composition of the *longissimus dorsi* muscle as of lamb carcasses, had great precision and accuracy. Although kilograms of fat on *longissimus dorsi* muscle and ash on the edible portion of cold carcasses had lower robustness than others parameters evaluated, their accuracy are acceptable. Hence, our hypothesis was confirmed, once the accessory BIA variables in the models explained most part of the variation of all lamb parameters analyzed. Additionally, *longissimus dorse* muscle showed good perspective of predicting the composition of the edible portion of lamb carcasses.

The soft tissues of lamb carcass are composed mostly by muscles and fat and they consist in the edible portion of the carcass. As the most abundant component in the soft tissue, water plays a critical role in meat quality which exists in and between muscle fibers (Li *et al.*, 2019). Thus, it is important to know the water content in the edible portion of carcass because it implies different effects on quality traits of meat. Lean meat generally contains 5% to 10% fat (Cashman & Hayes, 2017). At *longissimus dorsi* muscle, the intramuscular fat is the most expressive fat on its composition. This kind of fat is concentrated in clustered adipose cells and in homogeneously distributed within the muscle (Altmann & Pliquett, 2006). Lipids have also important role, mainly, which concerns aspects related to human nutrition and meat processing. They are poor electrical conductors (Berg & Marchello, 1994). However, the variation of impedance within the muscle clearly depends on the intramuscular fat (Altmann & Pliquett, 2006).

Making reference to red meat, it has particular nutritional properties including but not limited to the energy value and to the content of protein and fat, as well as the content of vitamins and minerals (Chikwanha, Vahmani, Muchenje, Dugan, & Mapiye, 2018; de Andrade, de Aguiar Sobral, Ares, & Deliza, 2016). A nutrition claim within Europe, on the basis of food composition tables, suggests that at least 20% of the

energy value is provided by protein (Cashman & Hayes, 2017). As a result, it is important to know the lamb composition given its being an essential component of human diets in several populations, providing high-quality nutrients. Transferring this information to the consumers can be a stronger platform to make lamb more competitive with others meat alternatives. Moreover, verifications of accomplishments of production and processing procedures, product quality and safety, accompanied by labels, which should include the meat nutritive value are also important (Díaz *et al.*, 2011; Montossi *et al.*, 2013). The use of bioimpedance technology to predict body or carcass composition is a cost-effective alternative to expensive proximate composition or energy density measurements (Hartman *et al.*, 2015). According to Hartman, Phelan, & Rosendale (2011), the estimative of carcass composition using BIA was 2.4–5.1% of the cost using traditional proximate composition analytical methods. This relative cost suggests 20–40 times more observations can be gathered using BIA than could be processed using analytical methods. Therefore, BIA showed to be a simple, objective, cheap, and clean method of evaluating the lamb composition.

5. Conclusion

Bioimpedance analysis showed to be a promising technology to replace expensive traditional methods of assessing physical, chemical, and nutritional parameters from lamb. Both the composition of *longissimus dorsi* muscle as the edible portion of lamb carcasses were predicted with high accuracy though BIA. Moreover, *longissimus dorsi* muscle was indicate to estimate the edible portion of lamb carcasses by BIA.

Conflict of interest

All authors have none conflict of interest to declare.

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Table 1 Descriptive statistics of bioimpedance analysis and lamb parameters.

	n	Min	Max	Mean	SD
Bioimpedance analysis					
Resistance, Ω	31	459.0	1236.0	709.5	164.5
Reactance, Ω	31	126.0	479.0	324.4	80.40
Impedance, Ω	31	515.7	1266.4	784.1	164.4
Phase angle, º	31	12.11	32.65	24.93	5.700
Bioelectric volume, cm^2/Ω	31	1.050	3.390	2.245	0.525
Resistive density, $kg^2/cm^2\ \Omega$	31	0.012	0.098	0.048	0.024
Reactive density, $kg^2/cm^2\ \Omega$	31	0.003	0.046	0.024	0.013
Longissimus dorsi muscle					
Weight, kg	31	0.150	0.500	0.320	0.100
Length, cm	31	31.00	46.00	39.05	3.831
Moisture, kg	31	0.115	0.386	0.243	0.074
Ash, kg	31	0.002	0.006	0.003	0.001
Protein, kg	31	0.030	0.099	0.063	0.020
Fat, kg	31	0.003	0.017	0.009	0.004
Lean mass, kg	31	0.145	0.485	0.306	0.094
Energy, MJ	31	0.830	3.040	1.875	0.660
Edible portion of carcass					
Soft tissue, kg	31	5.072	14.60	9.706	2.577
Moisture, kg	31	3.551	8.591	6.155	1.328
Ash, kg	31	0.052	0.128	0.087	0.019
Protein, kg	31	0.976	2.645	1.832	0.467
Fat, kg	31	0.493	2.496	1.348	0.607
Lean mass, kg	31	4.527	11.09	7.938	1.765
Energy, MJ	31	42.42	157.6	96.69	34.99

n = Sample size; Min = Minimum; Max = Maximum; SD = Standard deviation.

Table 2 Simple correlation between bioimpedance parameters and composition of the *longissimus dorsi* muscle and edible portion of lamb carcasses.

	Rs, Ω	Xc, Ω	Z, Ω	PA, °	V, cm^2/Ω	RsD, $kg^2/cm^2\ \Omega$	XcD, $kg^2/cm^2\ \Omega$
Longissimus dorsi muscle							
Moisture, kg	-0.148	0.524**	-0.044	0.609***	0.667***	0.904***	0.948***
Ash, kg	-0.213	0.392*	-0.126	0.543**	0.664***	0.829***	0.880***
Protein, kg	-0.145	0.546**	-0.035	0.624***	0.667***	0.886***	0.938***
Fat, kg	-0.163	0.455*	-0.072	0.538**	0.508**	0.783***	0.822***
Lean, kg	-0.148	0.530**	-0.042	0.614***	0.669***	0.903***	0.949***
Energy, MJ	-0.131	0.553**	-0.022	0.610***	0.667***	0.887***	0.935***
Edible portion of carcass							
Soft tissue, kg	-0.202	0.481**	-0.104	0.623***	0.700***	0.835***	0.883***
Moisture, kg	-0.172	0.508**	-0.071	0.633***	0.670***	0.829***	0.876***
Ash, kg	-0.141	0.323	-0.081	0.438*	0.583***	0.745***	0.711***
Protein, kg	-0.190	0.482**	-0.093	0.614**	0.683***	0.841***	0.881***
Fat, kg	-0.240	0.552**	-0.122	0.694***	0.720***	0.814***	0.898***
Lean, kg	-0.178	0.503**	-0.077	0.631***	0.676***	0.835***	0.880***
Energy, MJ	-0.195	0.529**	-0.087	0.637***	0.596***	0.853***	0.911***

Rs = Resistance; Xc = Reactance; Z = Impedance; PA = Phase angle; V = Bioelectrical volume; RsD = Resistive density; XcD = Reactive density.

Table 3

Predictive models of the lamb composition through bioimpedance analysis.

	Models	Calibration				Cross-validation		
		R^2	RMSE	Cp	*P*-value	R^2	RMSEP	CCC
Composition of longissimus dorsi muscle								
Moisture, kg	Y = - 0.05430 + 0.06931V + 2.32380RsD + 0.000039Z	0.991	0.0077	6.67	< 0.0001	0.985	0.0088	0.993
Ash, kg	Y = 0.00122 + 0.07007XcD + 0.00094V - 0.000063PA	0.883	0.0004	3.21	< 0.0001	0.830	0.0004	0.909
Protein, kg	Y = - 0.02067 + 0.01953V + 0.60060RsD + 0.000014Z	0.966	0.0039	2.61	< 0.0001	0.957	0.0041	0.978
Fat, kg	Y = 0.00267 + 0.27840XcD	0.675	0.0026	0.70	< 0.0001	0.627	0.0027	0.787
Lean mass, kg	Y = - 0.07490 + 0.08884V + 2.92440RsD + 0.000052Z	0.991	0.0093	4.84	< 0.0001	0.986	0.0111	0.993
Energy, MJ	Y = - 0.9840 + 0.66420V + 19.600RsD + 0.000542Z	0.972	0.1175	1.90	< 0.0001	0.961	0.1284	0.980
Composition of the edible portion of carcass								
Soft tissue, kg	Y = 0.9980 + 2.40500V + 74.4500RsD	0.917	0.7676	3.47	< 0.0001	0.885	0.8576	0.940
Moisture, kg	Y = 1.8900 + 1.1740V + 39.010RsD	0.880	0.4810	7.19	< 0.0001	0.849	0.5110	0.920
Ash, kg	Y = - 0.0246 + 2.0330RsD + 0.0223V - 3.3390XcD + 0.0018PA	0.828	0.0086	3.22	< 0.0001	0.742	0.0096	0.858
Protein, kg	Y = 0.2440 + 0.4253V + 14.000RsD	0.908	0.1494	4.11	< 0.0001	0.883	0.1593	0.939
Fat, kg	Y = - 0.1770 + 33.490XcD + 0.3880V	0.869	0.2286	0.27	< 0.0001	0.824	0.2492	0.906
Lean mass, kg	Y = 2.1340 + 1.5990V + 53.010RsD	0.894	0.6107	7.01	< 0.0001	0.866	0.6490	0.930
Energy, MJ	Y = - 16.000 + 29.830V + 1105.0RsD	0.882	12.528	0.24	< 0.0001	0.837	13.899	0.914

R^2 = Coefficient of determination; RMSE = Root mean squared error; Cp = Mallows Cp statistic; RMSEP = Root mean squared error of prediction; CCC = Concordance correlation coefficient.

V = Bioelectrical volume; RsD = Resistive density; Z = Impedance; XcD = Reactive density; PA= Phase angle

5 DISCUSSÃO GERAL

As diferenças no peso de abate dos cordeiros resultaram em ampla variação nos pesos de carcaças e, consequentemente, nos componentes da porção comestível da carcaça e de seus cortes. Estudos realizados com bioimpedância elétrica para estimar a composição da carcaça de cordeiros tiveram maior (JENKINS; LEYMASTER; TURLINGTON, 1988; SILVA *et al.*, 2018) e menor (ALTMANN *et al.*, 2004; BERG *et al.*, 1997; BERG; MARCHELLO, 1994; HEGARTY *et al.*, 1998; SLANGER *et al.*, 1994) variação nos pesos de carcaça que no presente estudo. De acordo com Jenkins *et al.* (1988) diferentes tipos de cordeiros com diferentes padrões de deposição de gordura são indispensáveis para avaliar a utilidade e robustez da BIA. Essa técnica deve produzir estimativa precisa em diversos tamanhos de carcaça para refletir a realidade das carcaças e dos cortes nas indústrias frigoríficas, atacadistas e no varejo (THOMSON *et al.*, 1997).

Além da diferença no peso de abate dos cordeiros ter influenciado na composição da carcaça, também foi observada ampla variação nas leituras da BIA nas carcaças quente e fria, nos cortes e no músculo *longissimus dorsi*. De acordo com Slanger *et al.* (1994), os valores médios medidos de Rs e Xc foram 2,03 e 2,26 vezes mais altos na carcaça fria do que na carcaça quente de cordeiros. Valores semelhantes aos desses autores foram descritos por Berg e Marchello (1994) e Berg *et al.* (1997). Os resultados deste estudo mostraram maior acréscimo nos valores de resistência (3,68) e de reatância (5,08) na carcaça fria em comparação à carcaça quente do que os valores apresentados pelos autores supracitados. Essa diferença pode ser atribuída à menor variação nos componentes da carcaça e ao local de avaliação da BIA. Essas análises foram realizadas na região dorsal da carcaça de cordeiros, com menor volume avaliado. De acordo com Lukaski (2013), em um condutor uniforme, com geometria e composição constantes, a impedância está relacionada diretamente ao produto da resistividade específica e comprimento do condutor, e indiretamente à área de seção transversal do condutor. Esse fato explica, também, os valores médios nos cortes serem menores que na carcaça fria.

As diferenças entre carcaça quente e fria eram esperadas porque a condutância diminui com a redução da temperatura (BERG; MARCHELLO, 1994). Nas carcaças quentes, nenhuma modificação na membrana ou no compartimento extracelular ocorre imediatamente após o abate e a temperatura é estável. A

condutância elétrica de um organismo é determinada por seus compartimentos de água e solutos dentro dessas áreas (DUNCAN *et al.*, 2007). Durante o período de rigor mortis, o pH, a temperatura e as modificações metabólicas influenciam nas propriedades elétricas da carne. Além disso, muitas mudanças ocorreram no músculo durante o processo de maturação da carne (DAMEZ *et al.*, 2008). A perda de fluidos após o abate e as alterações na distribuição de eletrólitos entre os compartimentos intracelular e extracelular na carcaça podem explicar o aumento das medidas de Rs e Xc da carcaça quente para a carcaça fria (MARCHELLO *et al.*, 1999; SLANGER *et al.*, 1994).

As temperaturas da carcaça quente e fria foram testadas como variáveis independentes e, devido à sua pequena contribuição para o poder de predição, apenas na carcaça quente, foram eliminadas. Da mesma forma, Berg *et al.* (1997) obtiveram uma pequena contribuição nos modelos de predição de massa magra (3%), apenas na carcaça quente de cordeiros. No entanto, as medições foram realizadas em ampla faixa de temperatura da carcaça resfriada, o que torna os modelos mais robustos e, portanto, aplicáveis em diversos ambientes. Para medir a temperatura das carcaças ou dos cortes é necessário equipamento apropriado, pessoa treinada e maior tempo é despendido. Neste sentido, medições rápidas são necessárias, já que o tempo é contado na logística e na economia das indústrias (HARTMAN *et al.*, 2015).

É importante ressaltar que, embora não tenha sido medida a temperatura nos cortes regionais, as medidas de BIA foram realizadas prontamente após a realização das análises da BIA na carcaça fria e da separação dos cortes. Considerando o curto tempo entre as medições e ambiente climatizado, a temperatura de avaliação nos cortes, provavelmente, ficou próxima à da carcaça fria. No músculo *longissimus dorsi*, os valores médios de Rs e Xc foram 3,78 e 5,36 vezes maiores em relação aos do costilhar e 1,20 vezes menor e 1,75 vezes maior em relação aos valores na carcaça fria, respectivamente. No entanto, os valores médios do V no músculo *longissimus dorsi* foram 2,48 e 1,63 vezes menores, enquanto os de PA foram 2,00 e 1,95 vezes maior que no costilhar e na carcaça fria, respectivamente. Os resultados podem ser explicados pelas diferenças nas medidas biométricas (peso e comprimento), na forma e na composição desses três parâmetros analisados. Sendo que, os valores médios percentuais de umidade (moisture), gordura (fat) e massa magra (lean) no músculo *longissimus dorsi* foram de 77%, 3% e 96%, respectivamente. Esses mesmos

componentes percentuais na carcaça fria apresentaram médias de 65%, 15%, e 84% e no costilhar de 64%, 17% e 83%, respectivamente (Tabela 1 - Apêndice 1).

Embora a temperatura tenha influenciado as diferenças entre as leituras de BIA nas carcaças quente e frias, a magnitude e o a significância das correlações foram semelhantes. A reatância medida na carcaça quente apresentou correlação positiva com todos os parâmetros avaliados, que variou de 0,54 até 0,62. Por sua vez, embora tenham sido encontradas correlações semelhantes entre resistência e a impedância medidas na carcaça fria e os mesmos parâmetros analisados, elas foram negativamente correlacionadas (-0,48 até -0,57). Berg *et al.* (1997) relataram correlações mais baixas comparado aos resultados deste estudo, sendo que, apenas a resistência foi correlacionada negativamente com a massa magra na carcaça quente (-0,38) e na carcaça fria (-0,41). Correlações semelhantes entre essas medidas da BIA e os componentes da carcaça foram relatadas em bovinos (ZOLLINGER *et al.*, 2010) e suínos (SWANTEK *et al.*, 1992). Por outro lado, Altmann *et al.* (2004) relataram correlações maiores aos do presente estudo, entre resistência, reatância e impedância com os componentes percentuais da carcaça de cordeiros. Diferentemente do ocorrido nas carcaças, no músculo *longissimus dorsi* apenas a reatância, entre estas três variáveis, foi correlacionada com os mesmos parâmetros avaliados no próprio músculo e na carcaça fria de cordeiros.

A Rs e Xc medidas, foram utilizados para derivar outras equações de propriedades elétricas, como PA, V, RsD e XcD, representando diferentes aspectos de como a corrente flui através da carcaça. O ângulo de fase é facilmente calculado através da relação arco-tangente da reatância e resistência ($PA = \tan^{-1} Xc/Rs) \times 180º/\pi$) e pode variar de zero grau (circuito resistivo, sistema sem membrana celular) a 90 graus (circuito capacitivo, sistema com predomínio de membrana celular) (CINTRA *et al.*, 2010). O PA, em humanos, é considerado indicador de saúde celular, como quantidade e funcionalidade celular, integridade da membrana celular e a sua variação indica alterações na composição corporal (NORMAN *et al.*, 2012). O PA, obtido através de medidas da BIA in vivo, foi utilizado nos modelos preditores da quantidade de proteína e massa magra da carcaça de cordeiros (MORO *et al.*, 2019a). O uso do PA, assim como do V, resultou em altas correlações com os componentes da carcaça, tanto na carcaça quente e fria como no músculo *longissimus dorsi*.

Os estudos de impedância realizados em humanos fazem uso de uma equação de predição do volume baseada na Lei de Ohm, em que, a impedância é diretamente

relacionada ao produto da resistividade específica (ρ) e o comprimento do condutor (L) e indiretamente à área da seção transversal do condutor (LUKASKI, 2013). Lukaski *et al.* (1985) explicaram detalhadamente a manipulação matemática da Lei de Ohm até chegar nas derivações utilizando a impedância ($V = \rho L^2/Z$) ou a resistência ($V = \rho L^2/Rs$) nos modelos para a predição do volume do condutor. A resistividade específica é uma propriedade elétrica específica de cada condutor, independentemente do tamanho ou forma do material. Nos condutores biológicos a ρ varia dependendo da microestrutura do tecido, do estado de hidratação e da concentração de íons eletrolíticos. No entanto, mesmo sabendo que cada tecido apresenta uma resistividade elétrica específica ela é considerada uma constante e é negligenciada nas equações de volume (BERG; MARCHELLO, 1994; JENKINS; LEYMASTER; TURLINGTON, 1988; SILVA *et al.*, 2018; SWANTEK *et al.*, 1992; ZOLLINGER *et al.*, 2010).

Os volumes, utilizando a Z ou Rs, foram testados como variáveis preditoras e explicaram uma pequena parte da variação da quantidade de músculo, umidade, proteína e massa magra na composição da carcaça de cordeiros, com resultados ligeiramente superiores para o volume calculado através da Rs (SILVA *et al.*, 2018). Coeficientes de correlações semelhantes aos resultados deste estudo foram relatados entre as medidas de volume e componentes da carcaça de suínos (SWANTEK *et al.*, 1992) e inferiores em carcaças de bovinos (ZOLLINGER *et al.*, 2010). Através das análises de correlações realizadas, verificou-se que os componentes da carcaça de cordeiros foram melhor correlacionados com as variáveis medidas de Rs e Xc quando estas foram relacionadas o volume do condutor. No entanto, quando elas foram relacionadas à densidade do material condutor, maiores correlações foram obtidas. A densidade resistiva foi obtida através da relação da massa e do volume bioelétrico do condutor (RsD = peso do material condutor^2/{comprimento do material condutor^2/Rs}). Enquanto que a densidade reativa foi estimada através da relação da massa e do comprimento do condutor com a reatância (XcD = peso do material condutor^2/{comprimento do material condutor^2/Xc}). No entanto, a RsD está relacionada à resistividade iônica do material condutor, sendo que quanto menor for a resistividade, mais facilmente o material permite a migração de íons livres através dos fluidos intra e extracelulares. Já a XcD está relacionada à permissividade e, consequentemente, à susceptibilidade elétrica, que determinam a habilidade do material de se polarizar em resposta a um campo elétrico e armazenar energia por um

determinado período. Sendo assim, as membranas celulares funcionam como capacitores elétricos e uma alta permissividade do dielétrico faz com que uma mesma quantidade de carga elétrica seja “armazenada” por menor tempo, levando a uma maior capacitância do material condutor. Essas variáveis foram inicialmente descritas por Zollinger *et al.* (2010) em carcaças de bovinos e resultaram em correlações superiores comparadas àquelas entre os mesmos componentes e apenas a Rs ou Xc. Semelhante comportamento se deu entre essas variáveis medidas in vivo e os constituintes quantitativos e percentuais da carcaça de cordeiros (MORO *et al.*, 2019a). No entanto, as fortes correlações existentes entre RsD e XcD e os parâmetros da carcaça provavelmente se devem ao fato da densidade estar altamente associada à composição da massa mole quando esses componentes são representados em quilogramas de peso da carcaça ou de seus cortes e não em porcentagem, como sugerido por Zollinger *et al.* (2010).

Essas altas correlações explicaram a utilização de pelo menos uma dessas variáveis na grande parte dos modelos de predição obtidos. A densidade resistiva contribuiu mais para explicar a variação dos nutrientes da carne de cordeiro na carcaça quente. Por sua vez, a XcD foi mais significativa nos modelos para prever os mesmos parâmetros na carcaça fria. No entanto, nos modelos de predição da composição dos cortes e no músculo *longissimus dorsi*, para estimar as suas próprias composições e também quando usadas para estimar a composição da carcaça, esse comportamento não foi o mesmo. Sendo que, para um determinado corte, a RsD ou a XcD explicou a maior parte da variação de um de seus componentes e isso não aconteceu nos outros cortes. O V foi utilizado em praticamente todos os modelos de predição apresentados, salvo nos modelos de predição de gordura no pernil e no músculo *longissimus dorsi*, e minerais no costilhar e na paleta. Esses modelos foram estimados através da XcD e/ou Xc apenas. Além desses, o modelo para estimar a composição de gordura na carcaça, através da BIA na paleta, utilizou apenas a XcD, Xc e RsD, e juntos contabilizaram 95% de sua variação na carcaça.

Nos modelos bioestatísticos de predição desenvolvidos, o uso de variáveis da BIA, e principalmente da densidade resistiva e/ou reativa, explicaram a maior parte da variação dos componentes na carcaça ou nos seus cortes. Essa variação, nos modelos de predição da BIA tanto na carcaça quente quanto na carcaça fria, foi de 86 % até 99%. Outros estudos de carcaça de cordeiro envolvendo BIA foram responsáveis por 79% e 78% (BERG; MARCHELLO, 1994) e por 72% e 77% (BERG

et al., 1997) da variação no peso da massa magra nas carcaças quentes e frias, respectivamente. Slanger *et al.* (1994) relataram que as medidas da BIA tanto na carcaça quente como na fria, apresentaram bom potencial para estimar o peso total dos cortes comercializáveis. Até o vigente momento, não houve estudos utilizando a BIA em cortes menores em carcaças de cordeiros. No entanto, a BIA foi utilizada em cortes primários de bovinos para estimar os tecidos moles e massa livre de gordura desses cortes, com coeficiente de variação ajustado variando de 89% até 97% (SLANGER; MARCHELLO, 1994). Esses autores utilizaram o peso, distância entre os eletrodos, temperatura, resistência e reatância como variáveis preditoras. De acordo com os autores, a temperatura não foi sempre significante estatisticamente, porém, a sua inclusão nos modelos resultou em valores de Cp de Mallows próximo do ideal. Os resultados obtidos nos cortes da carcaça de cordeiros, com a utilização de variáveis acessórias da BIA, foram superiores aos relatados nos cortes de bovinos, uma vez que os modelos de predição da massa dos tecidos moles e da massa magra dos cortes apresentou R^2 variando de 98,9% até 99,9% e de 95,2% até 98,1%, respectivamente. A quantidade de minerais nos cortes, de uma maneira geral, foi o componente que apresentou a menor potencialidade de predição. As variáveis da BIA nos cortes explicaram 68% no pernil, 53% no costilhar, 91% na paleta e 70% no corte do pescoço da variação da quantidade de minerais na massa mole desses cortes. Os demais componentes dos cortes regionais foram explicados por 86% até 99% com o uso das variáveis da BIA. Comportamento semelhante aconteceu quando utilizamos os dados da BIA segmentar para estimar a composição da carcaça fria de cordeiros. No entanto, o pescoço e a paleta foram os piores e melhores cortes representativos da composição da carcaça de cordeiros, respectivamente. A BIA no músculo *longissimus dorsi*, estimou os componentes no próprio músculo com maior precisão que os mesmos componentes na carcaça, exceto a quantidade de gordura. As correlações encontradas entre as variáveis da BIA e esses componentes no músculo e na carcaça explicam esses resultados. Modelos de predição da porcentagem de gordura intramuscular através da espectroscopia de impedância não foram eficientes na estimativa desse componente no músculo *longissimus dorsi* de suínos (R^2 = 0,12) e bovinos (R^2 = 0,48) (ALTMANN; PLIQUETT, 2006). No entanto, Slanger e Marchello (1994) relataram melhores resultados (R^2 = 0,83) no músculo *longissimus dorsi* de bovinos para predizer a porcentagem de marmoreio com o uso da impedância monofrequencial (800 uA e 50 kHz). O modelo de predição desenvolvido para estimar

a quantidade de gordura no músculo *longissimus dorsi* explicou 65,7% da variação desse constituinte no próprio músculo. Embora esse modelo tenha apresentado baixo RMSE e valor de Cp próximo do ideal, mais pesquisas devem ser conduzidas a fim melhorar a eficiência da BIA em estimar a quantidade de gordura da carne ovina e de outras espécies.

Uma equação de regressão robusta prediz com mais eficiência a variável dependente em ampla distribuição populacional. Assim, reduz o efeito de observações “outliers” que exercem forte influência na análise de regressão, deixando grandes os resíduos de observações influentes, tornando-os mais facilmente identificados pelo modelo preditivo (BERG; MARCHELLO, 1994). Na seleção de modelos de predição, alguns parâmetros estatísticos devem ser considerados para selecionar o melhor modelo preditivo. Neste estudo, foi considerado o maior R^2, o menor RMSE e o valor de Cp de Mallows menor ou mais próximo do número de preditores nos modelos mais um (constante). Um valor de Cp de Mallows que é próximo ao número de preditores mais a constante indica que o modelo é mais preciso, relativamente imparcial na estimativa dos verdadeiros coeficientes de regressão e na previsão de respostas futuras, com pequena variação (SLANGER; MARCHELLO, 1994). No entanto, estudos de validação cruzada são necessários para comprovar a previsibilidade do procedimento para carcaças de cordeiros e de seus cortes em condições variadas na indústria frigorífica. Para avaliar o ajuste desses modelos para cada conjunto de dados, utilizou-se uma abordagem de validação de exclusão única utilizando a soma da previsão de resíduos quadrados, conforme descrito por Hafs e Hartman (2011). Esses resíduos são estimados deixando de fora uma única observação subtraindo o resíduo do valor observado do valor predito por um modelo de regressão de predição com as demais observações. Esses modelos foram comparados com os resíduos estimados a partir do modelo de médias gerais, produzindo um R^2 de predição que indica o desempenho preditivo geral. Assim, a avaliação da adequação dos modelos só é possível por meio da combinação de diferentes parâmetros estatísticos e pela investigação adequada sobre os objetivos para os quais o modelo matemático foi inicialmente conceitualizado e desenvolvido (TEDESCHI, 2006). Neste sentido, três parâmetros principais (R^2, RMSEP e CCC) foram considerados na avaliação do grau de precisão e exatidão desses modelos. Portanto, os menores valores de erro quadrático médio da validação cruzada, maior correlação linear significativa entre os valores reais e os valores preditos e o coeficiente de correlação de concordância mais

próximo de 1 mostraram que os modelos apresentados são eficazes para estimar a maioria dos parâmetros avaliados nas carcaças, quente e frias, nos cortes e no músculo *longissimus dorsi*. Embora alguns modelos preditivos foram melhores que outros, tais como, para estimar os tecidos moles e minerais, nas carcaças e nos cortes, respectivamente, eles apresentaram precisão aceitáveis.

Sendo assim, a utilização da densidade resistiva e/ou da densidade reativa foi essencial para estimar componentes físico, químicos e nutricionais, na carcaça quente e na fria. No entanto, na carcaça fria, esses modelos de predição se mostraram ligeiramente mais precisos que nas carcaças quentes de cordeiros. Uma vantagem de avaliar a BIA na carcaça fria é que a perda de peso da carcaça quente para a fria depende de vários fatores, tais como, o manejo da carcaça, a uniformidade e a espessura da gordura subcutânea e a temperatura de resfriamento (DOS SANTOS *et al.*, 2019). Assim, as medições de BIA na carcaça fria podem compensar esses possíveis fatores. Além disso, as avaliações de carcaça fria representaram melhor a composição real da parte comestível da carcaça. Esses resultados podem levar ao desenvolvimento de programas de pagamento por mérito da carcaça (MARCHELLO *et al.*, 1999).

Em relação aos cortes, a BIA segmentar foi eficiente em estimar a composição em cada corte regional e a paleta foi o corte que melhor representou a composição da carcaça. Desta forma, a análise de BIA pode ser realizada em cortes menores. Através desses resultados, o rendimento dos componentes dos cortes ou da carcaça também podem ser estimados e, portanto, a BIA segmentar pode ser usada nesse sistema de precificação por qualidade do corte ou da carcaça e também por produtos processados de carne ovina (SLANGER; MARCHELLO, 1994). A diferenciação do produto, incluindo cortes menores, de fácil preparo, informações nutricionais e de agregação de valor podem determinar o melhor destino para as carcaças de ovinos ou de seus cortes e reduzir as perdas econômicas para as indústrias e consumidores (ZHAO *et al.*, 2017). Em humanos, a BIA segmentar fornece estimativas indiretas da composição corporal cujo desafio é atingir a precisão e exatidão das técnicas de referência, como densitometria, imagem de ressonância magnética ou absorciometria por raios-x de dupla energia (KHALIL; MOHKTAR; IBRAHIM, 2014; WARD, 2012). Nos cortes das carcaças de cordeiro, essa técnica foi referida às análises químicas reais de cada corte e de toda a carcaça, portanto, sua precisão deve ser maior que as análises de BIA em humanos.

Da mesma forma, a utilização da BIA no músculo *longissimus dorsi* mostrou-se eficiente alternativa para substituir métodos tradicionais analíticos de avaliação da composição da carne de cordeiro, como os para determinar umidade, cinzas, proteínas e gordura. A BIA é uma técnica rápida, objetiva, não destrutiva, minimamente invasiva e que não utiliza produtos químicos nocivos. Além do mais, o uso da tecnologia de bioimpedância para prever a composição química da carne é uma alternativa econômica às medidas de composição analíticas (HARTMAN *et al.*, 2015). Tanto a BIA segmentar como a BIA realizada no músculo *longissimus dorsi* apresentam excelente potencial para estimar a composição dos tecidos moles da carcaça de cordeiros. No entanto, os modelos de predição desenvolvidos a partir da BIA segmentar nos cortes (artigo 2) e no músculo *longissimus dorsi* (artigo 3) não superaram a precisão e exatidão dos modelos de predição oriundos da análise da BIA realizada tanto na carcaça quente como na carcaça fria (artigo 1). As medidas de BIA obtidos nas carcaças, nos cortes e no músculo *longissimus dorsi* foram coletados de uma maneira prática para aplicação por pesquisadores ou industrial. A metodologia proposta, especialmente no músculo *longissimus dorsi*, envolve a sua extração das carcaças frias. Do ponto de vista da aplicabilidade, embora esse procedimento pareça ser mais aplicável em centros de pesquisa do que na indústria, ele é rápido e fácil de ser executado. As medidas da BIA trazem grandes benefícios por serem rápidas, exigindo equipamentos relativamente baratos e capazes de incorporação e uso em um sistema em que o grau de treinamento do operador necessário seja mínimo (COSGROVE; KING; BRODIE, 1988). Portanto, assim como em centros de pesquisa, todos os segmentos da indústria de carne podem usar essa tecnologia. Desta forma, os resultados desta pesquisa podem contribuir com diversos elos da cadeia da carne ovina.

6 CONCLUSÃO GERAL

A BIA é uma técnica objetiva, simples, rápida, não destrutiva, que não utiliza componentes químicos nocivos e produz resultados precisos na estimativa de componentes físicos, químicos e nutritivos da carcaça de cordeiros e de seus cortes. A tecnologia da BIA pode ser facilmente incorporada em todos os segmentos da indústria da carne de cordeiros e em centros de pesquisas. As densidades resistivas e reativas foram essenciais para estimar a composição da porção comestível dos cortes e da carcaça de cordeiros. Os modelos de predição desenvolvidos através da análise da BIA realizada nas carcaças frias são mais precisos e exatos para estimar a composição da carcaça de cordeiros comparados a BIA segmentar, no músculo *longissimus dorsi* e nas carcaças quentes.

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APÊNDICE 1 - COMPARAÇÃO DE MÉDIAS DOS COMPONENTES PERCENTUAIS DA CARCAÇA FRIA, DOS CORTES REGIONAIS E DO MÚSCULO *LONGISSIMUS DORSI.*

	Carcaça fria	Pernil	Costilhar	Paleta	Pescoço	*Longissimus dorsi*	SEM*	*P*-value
Massa mole, %	81,14[a]	80,76[a]	81,57[a]	81,88[a]	79,09[b]	-	0,187	< 0.0001
Ossos, %	18,86[b]	19,24[b]	18,43[b]	18,12[b]	20,92[a]	-	0,187	< 0.0001
Umidade, %	65,27[bc]	65,59[bc]	64,08[c]	66,71[b]	66,02[bc]	76,69[a]	0,156	< 0.0001
Minerais, %	0,905[bc]	0,914[bc]	0,860[c]	0,981[b]	0,915[bc]	1,084[a]	0,013	< 0.0001
Proteína, %	18,93[abc]	19,27[ab]	18,53[c]	19,18[abc]	18,57[bc]	19,59[a]	0,060	< 0.0001
Gordura, %	14,90[ab]	14,23[b]	16,53[a]	13,13[b]	14,49[ab]	2,651[c]	0,168	< 0.0001
Massa magra, %	84,20[bc]	84,86[b]	82,61[c]	85,89[b]	84,60[bc]	96,27[a]	0,161	< 0.0001

* SEM = Erro padrão da média
Médias seguidas de letras diferentes na linha diferem ($P < 0,05$) pelo teste *F*

ANEXO A- COMPROVANTE DE SUBMISSÃO DO ARTIGO INTITULADO "ASSESSING THE COMPOSITION OF THE SOFT TISSUE IN LAMB CARCASSES WITH BIOIMPEDANCE AND ACCESSORY MEASURES".

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Anderson Moro <andersondazoo@gmail.com>

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Journal: Meat Science

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ANEXO B- CERTIFICADO DE APROVAÇÃO PELA COMISSÃO DE ÉTICA NO USO DE ANIMAIS DA UNIVERSIDADE FEDERAL DE SANTA MARIA

Comissão de Ética no Uso de Animais
da
Universidade Federal de Santa Maria

CERTIFICADO

Certificamos que o Projeto intitulado "Aplicação do método de Bioimpedância na avaliação tecidual (in vivo e na carcaça) e textura da carne de cordeiros", protocolado sob o CEUA nº 8259211015, sob a responsabilidade de **Cleber Cassol Pires** - que envolve a produção, manutenção e/ou utilização de animais pertencentes ao filo Chordata, subfilo Vertebrata (exceto o homem), para fins de pesquisa científica (ou ensino) - encontra-se de acordo com os preceitos da Lei 11.794, de 8 de outubro de 2008, com o Decreto 6.899, de 15 de julho de 2009, com as normas editadas pelo Conselho Nacional de Controle da Experimentação Animal (CONCEA), e foi **aprovado** pela Comissão de Ética no Uso de Animais Universidade Federal de Santa Maria (CEUA/UFSM) em reunião de 14/01/2016.

We certify that the proposal "Application of the Bioimpedance Method at tissue evaluation (in vivo and carcass) and texture of lambs meat", utilizing 32 Ovines (32 males), protocol number CEUA 8259211015, under the responsibility of **Cleber Cassol Pires** - which involves the production, maintenance and/or use of animals belonging to the phylum Chordata, subphylum Vertebrata (except human beings), for scientific research purposes (or teaching) - it's in accordance with Law 11.794, of October 8 2008, Decree 6899, of July 15, 2009, with the rules issued by the National Council for Control of Animal Experimentation (CONCEA), and was **approved** by the Ethic Committee on Animal Use of the Federal University of Santa Maria (CEUA/UFSM) in the meeting of 01/14/2016.

Vigência da Proposta: de 01/2015 a 03/2016 Laboratório: Zootecnia/ovinocultura

Procedência: Não aplicável

Espécie:	Ovinos	Gênero:	Machos	idade:	3 meses	N:	32
Linhagem:	Texel X Ile de France			Peso:	20 Kg		

Nota: A bioimpedância (BIA) é um método que aplica à tecnologia da impedância no estudo da composição corporal pela avaliação da diferença da condutividade elétrica dos tecidos. Os resultados da BIA são expressos pelas medidas primárias de resistência (R) e reatância (X). A possibilidade de estimar características de carcaça antes do abate. Identificar animais que estejam se aproximando do ponto ótimo de acabamento. Possibilitar a padronização de carcaças e consequentemente da qualidade da carne. Servir como ferramenta aos programas de melhoramento genético. Promoção do bem-estar humano e animal. Além da agilidade, economicidade de recursos em pesquisas são as principais vantagens do uso da BIA na ovinocultura. Neste sentido, o objetivo desta pesquisa será estabelecer equações que possam estimar os componentes teciduais da paleta, da carcaça e do animal in vivo pelo método BIA e avaliar as correlações com a textura dos músculos Longissimus dorsi e Triceps brachii. Serão utilizados 32 Cordeiros da raça Texel X Ile de France, com 5 meses de idade e peso vivo médio de 20 Kg. Em cada unidade experimental serão feitas as mesmas mensurações preliminares da BIA, sendo estas em dois locais anatomicamente diferentes e com dois tipos de eletrodos. Serão realizadas pré abate no cordeiro in vivo, e pós abate na carcaça quente e fria e na paleta. Para validar o método da BIA será feito dissecação e composição centesimal do animal post-mortem, da carcaça e da paleta. Os dados serão submetidos à analise de regressão e de correlação em nível de 5% de significância, utilizando o pacote estatístico SAS (2004).

Santa Maria, 18 de janeiro de 2016

Daniela B Leal

Profa. Dra. Daniela Bitencourt Rosa Leal
Coordenadora da Comissão de Etica no Uso de Animais
Universidade Federal de Santa Maria

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Horário de atendimento: das 8:30 às 11:30 e 14:00 às 16:30hs - e-mail: ceua.ufsm@gmail.com
CEUA Nº 8259211015