Hide and Seek: Enhancing Sustainability in Leather Production with Spectroscopic Technologies

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Abstract

The leather industry faces critical sustainability challenges, including inefficient detection of microbial spoilage in raw hides and inadequate supply chain traceability. Currently, no rapid spoilage detection techniques suitable for industrial practices exist, resulting in increased chemical use and waste. Furthermore, traceability systems for processed leather products often lack accuracy, leading to misrepresentation and eroding consumer trust.

This study addresses these issues with spectroscopic techniques. A linescan hyperspectral imaging system working in a spectral range of 550 nm to 1700 nm was utilized as a rapid and non-destructive technique for predicting the aerobic plate counts on raw hide samples during storage. Our models successfully predicted the staling states characterised by bacterial loads on hide samples with low prediction errors. Real-time grading based on microbial load offers potential for optimising raw hide selection for production pathways, reducing chemical consumption and preventing material waste. Additionally, visible-near infrared spectroscopy coupled with machine learning successfully traced wet-blue leather impregnated with chemical tracers. The classification models demonstrated over 97% accuracy in differentiating treated and untreated samples, ensuring reliable verification of origin and authenticity throughout the supply chain.

These results demonstrate the potential of spectroscopic technologies to enhance leather production sustainability by minimising waste, optimising resources, and ensuring supply chain transparency. This approach fosters environmentally responsible practices and aligns leather production with global sustainability goals.

Keywords: Leather, Traceability, Near-Infrared, Spectroscopy, Machine Learning, SVM

1. Introduction

Leather manufacturing transforms perishable hides and skins—by-products of the meat industry—into durable goods by stabilising the collagen matrix and preventing microbial degradation (Zhang et al., 2018). However, raw hides are vulnerable to microbial spoilage (also known as staling) during storage, particularly if preservation is inadequate. Despite existing preservation practices, spoilage often goes undetected until after tanning, leading to irreversible quality loss, increased chemical use, and material waste (Kahsay et al., 2015; Kuttalam et al., 2020). Traditional microbiological detection methods are slow, invasive, and unsuitable for industrial-scale application (Cockcroft & Redfern, 2015), underscoring the need for rapid, non-destructive alternatives (B. et al., 2018).

Simultaneously, supply chain traceability has become increasingly important in ensuring quality, transparency, and sustainability in leather production. Even in regions like New Zealand—renowned for ethical sourcing and high processing standards—globalisation challenges the maintenance of end-to-end transparency. Although consumers value leather's natural characteristics, they are often unaware of the environmental impacts associated with its production (Eisen et al., 2024; Rinaldi et al., 2022). Technologies that enhance both quality control and traceability are essential for aligning industry practices with sustainability goals.

Spectroscopic methods such as hyperspectral imaging (HSI) and visible to near-infrared (Vis-NIR) spectroscopy offer promising non-invasive solutions. HSI has been applied successfully to detect microbial spoilage in food systems (Braz et al., 2018; Cantero et al., 2007; Grasel & Ferrão, 2016) and biological matrices (Texas, 2015). Vis-NIR spectroscopy, especially when combined with machine learning (ML), has proven useful for classifying leather properties (Braz et al., 2018; Cantero et al., 2007), identifying tanning agents (Grasel & Ferrão, 2016), and predicting meat quality (van Rossum, 1995). Other traceability technologies—like DNA tagging and subsurface tattooing—have demonstrated potential but face technical limitations under harsh tanning conditions (Cataldo et al., 2016; Stenzel et al., 2015) In contrast, spectroscopic approaches are scalable, contactless, and well-suited to industrial integration.

This study investigates the use of Vis-NIR spectroscopy and HSI as a spectroscopy-based technologies for microbial spoilage detection and traceability in bovine hides. We hypothesise that: (1) Vis-NIR spectral features can distinguish staled hides from fresh ones; (2) chemical tracers embedded in wet-blue leather can be reliably detected using spectral signatures; and (3) matrix variability affects tracer detectability. These findings inform the development of a unified, sustainable quality control system for leather processing.

2. Materials and Methods

2.1 Preparation and Assessment of Raw Hide Spoilage

To simulate microbial spoilage, two fresh bovine hides were obtained from Tasman Tanning (Whanganui, New Zealand) and cut into ten square pieces (10 × 10 cm). Samples were evenly taken from the left and right sides along the backbone. The left-side samples were stored at 20 °C to accelerate spoilage, while the right-side samples were stored at 4 °C as a control. Over a three-day storage period, samples were assessed daily from both the grain and flesh sides.

Hyperspectral imaging (HSI) was performed using a Headwall Vis-NIR line-scan system covering 550–1700 nm with 235 spectral bands. The camera was calibrated using white (Teflon) and dark references. Exposure time, translation speed, and pixel size (~0.4 × 0.4 mm) were optimised to ensure image quality and avoid sensor saturation. Corresponding microbial loads were determined using aerobic plate counts (APC). A 1 cm² area on each sample was swabbed, vortexed in 0.1% peptone water, serially diluted, plated on agar, and incubated at 30 °C for 24 hours to enumerate colony-forming units (CFUs/cm²). At the end of storage, selected samples were processed into crust leather using LASRA's standard tanning protocol, and the grain surface was examined under an Olympus SZX7 microscope to detect spoilage-related degradation.

2.2 Prediction of Microbial Load Using PLSR Models

To predict microbial contamination from spectral data, reflectance spectra from each sample were averaged over the region of interest and subjected to pre-processing, including Standard Normal Variate (SNV) transformation, Savitzky–Golay smoothing, and first or second-order derivatives. Grain and flesh datasets were independently split into calibration (70%) and validation (30%) sets. Partial Least Squares Regression (PLSR) was used to model $\log_{10}$(APC), with five-fold cross-validation applied to optimise the number of latent variables. Model performance was evaluated using coefficients of determination (R^2), standard error of prediction (SEP), residual predictive deviation (RPD), and bias. Variable Importance in Projection (VIP) scores and regression coefficients were also calculated to identify key wavelengths associated with spoilage.

2.3 Sample Preparation for Traceability Assessment

To explore chemical tracer detection in leather, two batches of wet-blue samples were prepared. In Batch 1, one hide was halved, with three sections treated pre-tanning with either 5% collagen hydrolysate, 5% Cloisite Na^+, or 0.06% TCMTB, and three left untreated. Each section was cut into 100 sub-samples. Half of the untreated sub-samples were surface-treated post-tanning ("lab-processed"), and the rest remained untreated. This produced a total of 600 samples, which were used for exploratory principal component analysis (PCA).

Following Batch 1, TCMTB was selected for further study in Batch 2. Three hides from different animals were used to prepare treated (TCMTB) and control wet-blue samples. Each piece was scanned on both grain and flesh sides, generating 162 samples used for classification model development and validation.

2.4 Spectral Acquisition and Instrumentation

Spectral data were acquired using two instruments: the Sagitto miniaturised NIR spectrometer (900–1700 nm, 10 nm resolution) and the Labspec 4 benchtop Vis-NIR spectrometer (350–2500 nm, 3–10 nm resolution). All samples were scanned on both grain and flesh sides at room temperature (~20 °C). Spectra were referenced against white reflectance standards. Although the Trek instrument was used in Batch 1, those results are not reported here due to its unavailability in Batch 2.

2.5 Classification and Feature Selection

Spectra were pre-processed (SNV and derivatives), and Support Vector Machine (SVM) models were developed to classify treated and untreated leather. Separate models were built for each instrument (Sagitto or Labspec), side (grain or flesh), and kernel type (linear or radial basis function). Double cross-validation was implemented by alternating hide pieces between training and validation sets to reduce overfitting and test model generalisability. A total of 216 SVM models were created and compared based on classification accuracy and Cohen's kappa.

To enhance model interpretability, Genetic Algorithms (GAs) were employed to identify key wavelengths. GA-Random Forest models were trained over 100 generations with a population size of 20 and assessed using 10-fold cross-validation to determine internal prediction accuracy.

3. Results and Discussion

3.1 Detection of Spoilage in Raw Hides

3.1.1 Bacterial Enumeration and Microscopic Evidence

Spoilage in hides begins immediately after slaughter. Aerobic plate count (APC) data confirmed exponential bacterial growth, especially at 20 °C, simulating realistic spoilage conditions (Figure 1). Microscopy of crust leather (Figure 2) showed irreversible grain damage after three days at 20 °C, with corresponding APC values exceeding 10^{10} CFU/g. These results support practical microbial thresholds: 10^9 CFU/g for grain-side and 10^{10} CFU/g for the flesh side.

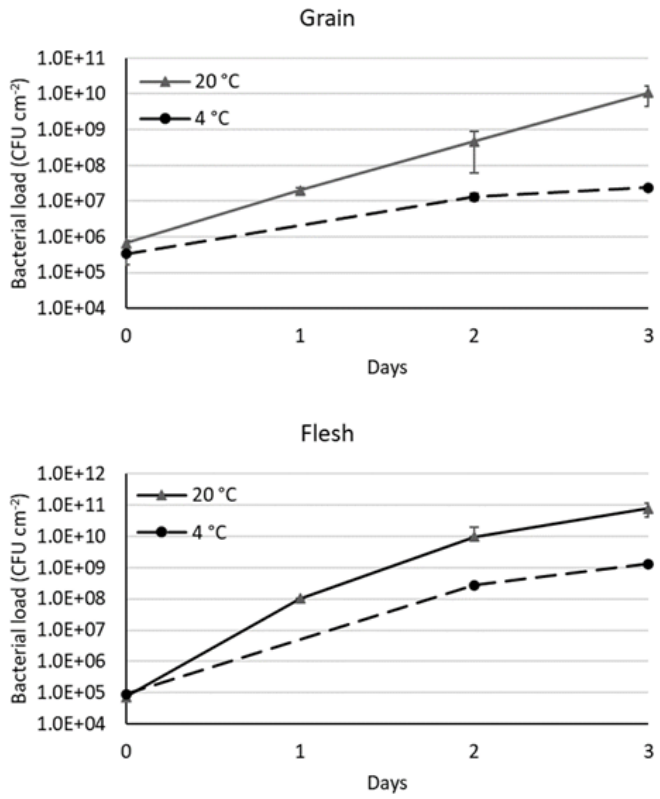

Figure 1. Aerobic plate counts for grain and flesh sides of hide samples.

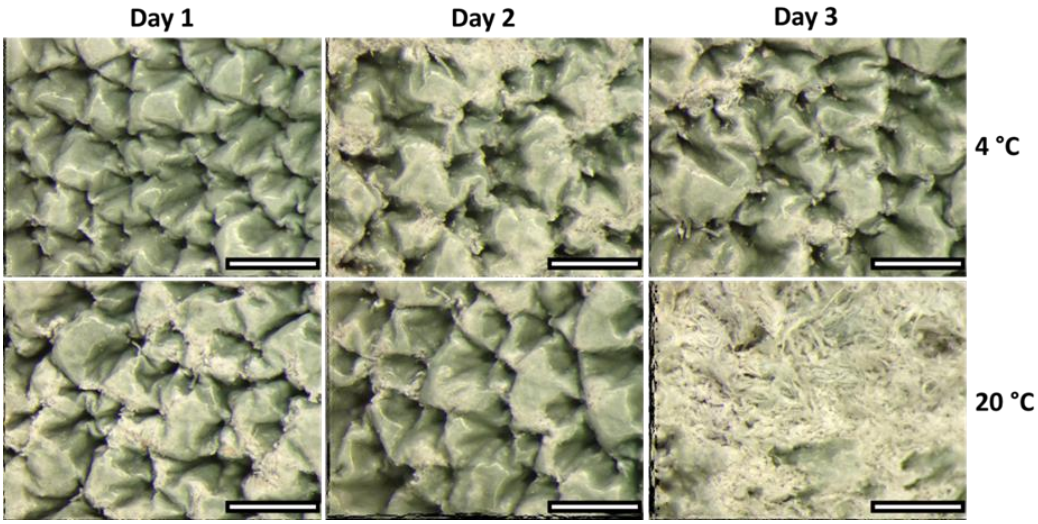

Figure 2. Representative microscopic images of grain surfaces. Scale bar, 0.5 mm

3.1.2 Spectral Signatures of Spoilage

SNV-transformed Vis-NIR spectra revealed degradation-linked absorbance bands at 970, 1200, and 1450 nm—corresponding to overtone vibrations in water, lipids, and proteins. Progressive spectral changes, particularly at higher storage temperatures, reflected chemical alterations in collagen and tissue due to microbial activity. Although no single feature uniquely indicates APC, the pattern of spectral evolution reliably tracks spoilage progression. For example, Figure 3a–b shows how absorbance intensities at 970, 1200, and 1450 nm increase as spoilage progresses, indicating water redistribution, lipid degradation, and

protein breakdown. The temporal trends in Figures 3c–f visually confirm that these spectral changes occur earlier and more dramatically at 20 °C than at 4 °C, supporting the technique's sensitivity to early microbial activity under varying storage conditions.

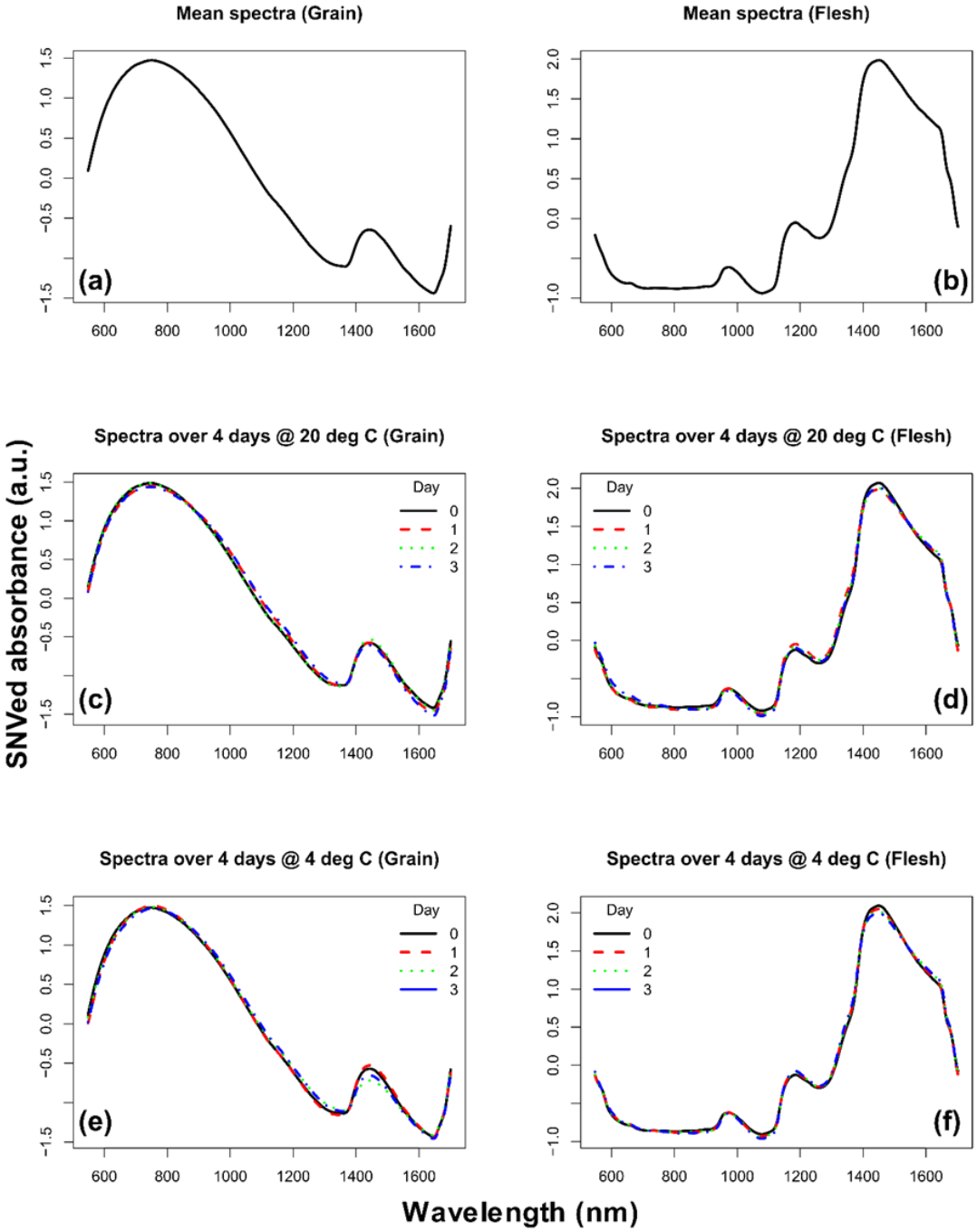

Figure 3. Absorbance spectra: (a) SNVed Mean spectra for grain side, (b) SNVed Mean spectra for flesh side, (c) SNVed spectra for sample 1 (hide 1) over 4 days @ 20 deg C on grain side, (d) SNVed spectra for sample 1 (hide 1) over 4 days @ 20 deg C on flesh side, (e) SNVed spectra for sample 6 (hide 2) over 4 days @ 4 deg C on grain side and (f) SNVed spectra for sample 6 (hide 2) over 4 days @ 4 deg C on flesh side.

3.1.3 Prediction of Microbial Load Using PLSR

Partial least squares regression (PLSR) models successfully predicted log-transformed APC values. The best results were achieved using first derivative preprocessing, with R^2 values up to 0.92 and RPD values exceeding 4.3 on the flesh side, indicating excellent predictive capacity (Table 1). Grain-side models also performed robustly (RPD ≈ 2.3).

Table 1. PLSR Model Performance for Microbial Load Prediction

Sample Side	R^2cv	RMSECV	RPD
Grain	0.88	0.37	3.76
Flesh	0.92	0.32	4.68

Prediction maps generated from SNV-processed spectra visualised microbial load progression over time, supporting real-time spoilage monitoring (Figure 4). These maps provide a spatial overview of bacterial colonisation across hide surfaces, allowing operators to identify hotspots of spoilage. Notably, samples stored at 20 °C showed rapid microbial proliferation by Day 2, while control samples at 4 °C retained low predicted counts. This visual capability can guide tanneries in prioritising processing or discarding individual hide sections based on real-time contamination patterns. These capabilities could help tanneries prioritise processing schedules and reduce waste.

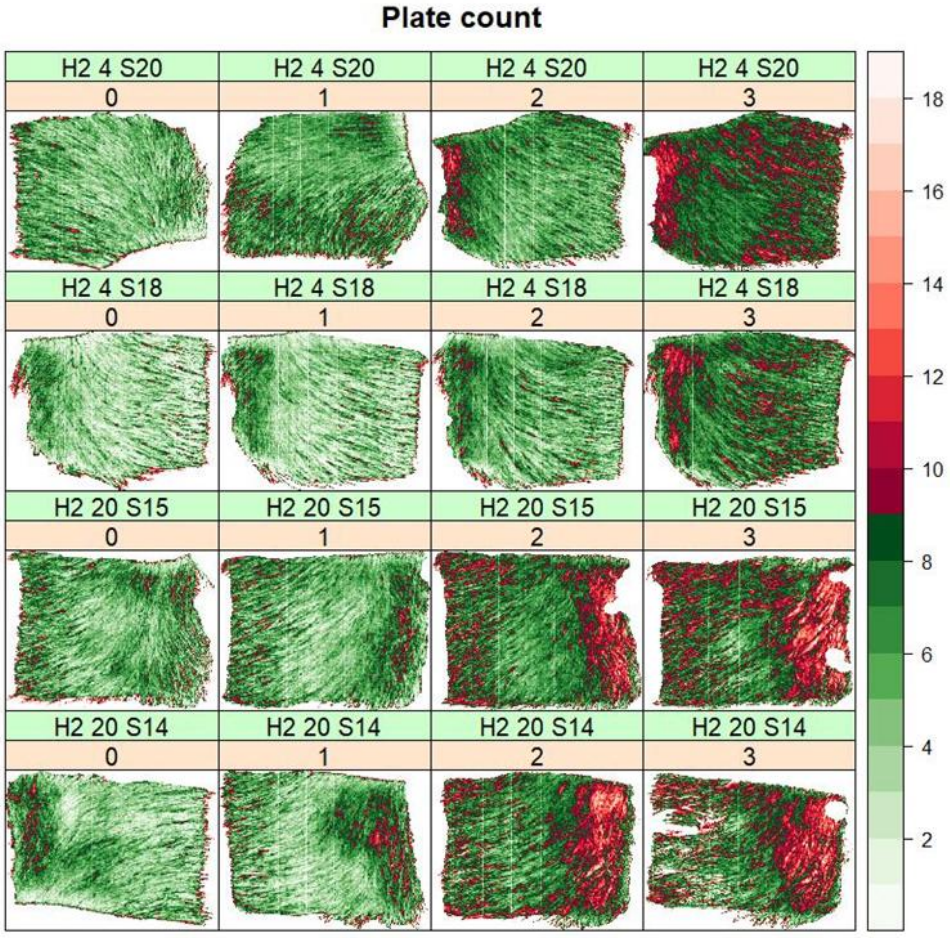

Figure 4. Prediction maps: spatial distribution of log 10 plate count for some of the hide 2 samples on grain side at both storage temperatures.

3.2 Detection of Chemical Tracers in Wet-Blue Leather

3.2.1 PCA for Tracer Detection

Principal component analysis (PCA) showed clear separation between control and treated samples using three tracer types (hydrolysate, Cloisite Na^+, TCMTB), particularly on the grain side. Spectral features near 950 nm, 1300–1500 nm, and 1700 nm are attributed to moisture, organic compounds, and chromium–tracer interactions (Figure 5-7). TCMTB-treated samples were least affected by temporal variation and chosen for further analysis.

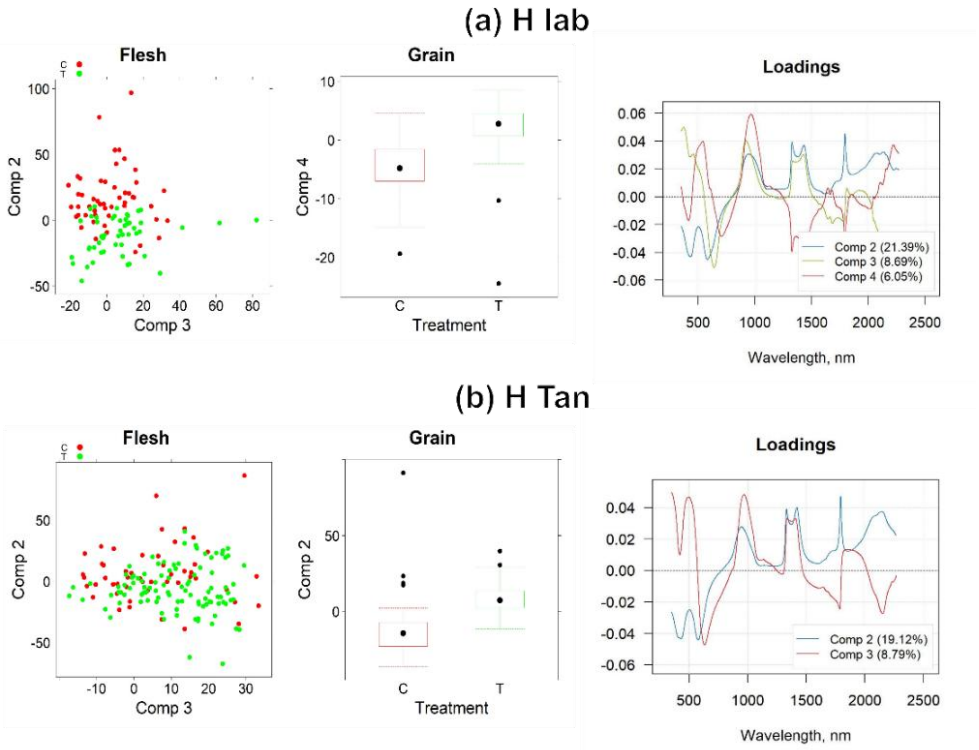

Figure 5. Comparing PCA models across tracers, treatment type (tannery or lab) and scanning side (Grain and Flesh: (a) Hydrolysate with lab processing and (b) Hydrolysate with tannery processing.

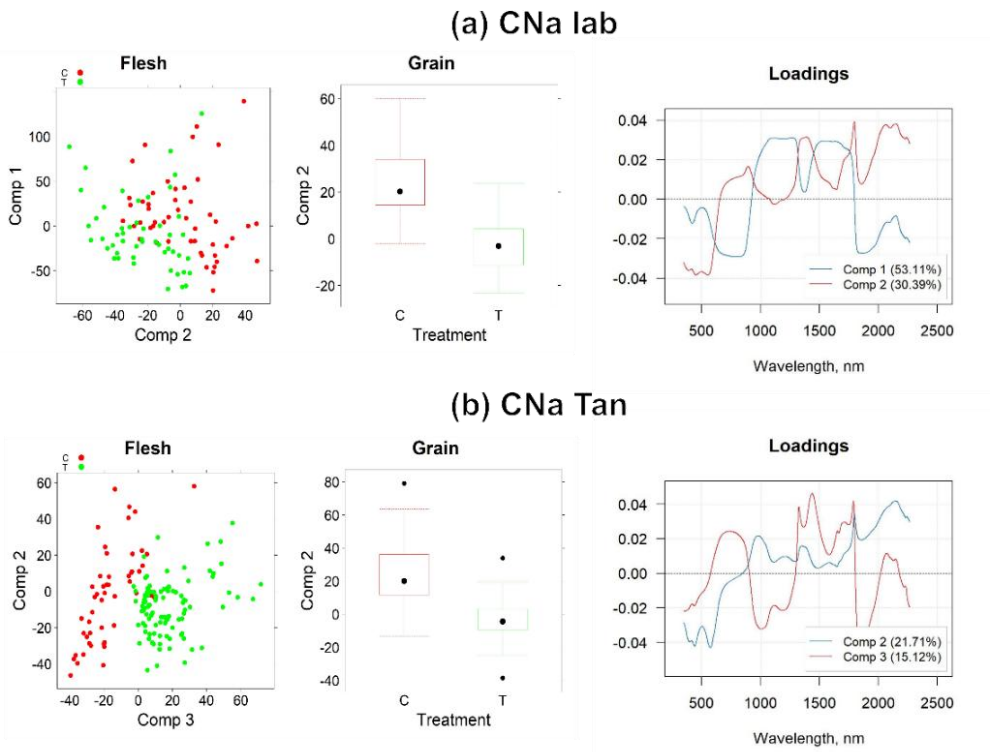

Figure 6. Comparing PCA models across tracers, treatment type (tannery or lab) and scanning side (Grain and Flesh: (a) Cloisite Na+ with lab processing and (b) Cloisite Na+ with tannery processing.

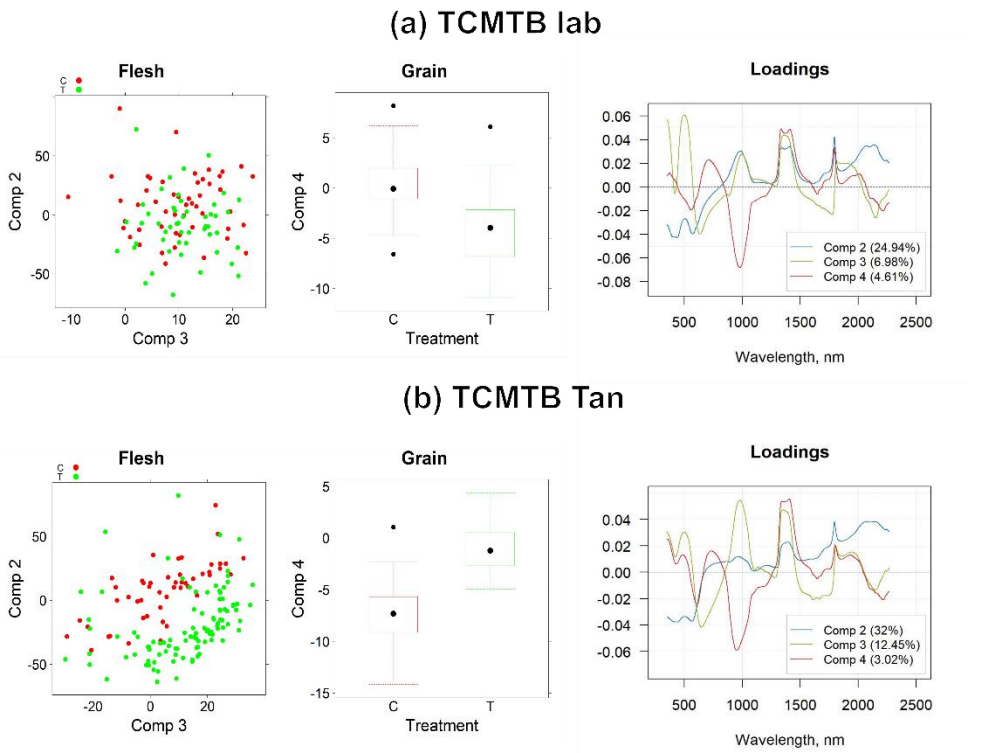

Figure 7. Comparing PCA models across tracers, treatment type (tannery or lab) and scanning side (Grain and Flesh: (a) 2-Thiocyanomethylthio benzothiazole with lab processing and (b) 2-Thiocyanomethylthio benzothiazole with tannery processing.

3.2.2 Summary of Classification and Feature Selection Insights

Preliminary classification models based on Vis-NIR spectra also demonstrated promising performance in distinguishing chemically treated leather from control samples. These models suggest that tracer signals are spectrally resolvable, particularly on the grain side, and support the feasibility of using compact spectrometers for real-time supply chain authentication. Further development and validation of these models are ongoing and will be reported in future peer-reviewed publications. Similarly, feature selection techniques have been explored to enhance model interpretability and identify key spectral regions linked to tracer presence, though detailed outcomes are withheld here pending formal publication.

3.3 Integrated Implications for Leather Research

Together, these findings demonstrate that Vis-NIR spectroscopy, augmented by chemometric modelling, can support an integrated approach to leather sustainability. Early-stage microbial load prediction enables more efficient raw material use and reduces the risk of defective output. Simultaneously, tracer detection may offer a viable pathway toward the verification of product origin, reinforcing transparency and consumer trust. These capabilities could transform leather production workflows by enabling real-time, non-destructive monitoring of both quality and authenticity.

These findings collectively support the initial hypotheses proposed in this study. First, the results confirmed that Vis-NIR spectral features can effectively distinguish between fresh and staled hides. The observed spectral changes corresponded closely with microbial load and visible grain degradation, thereby validating the hypothesis that spoilage progression is detectable through spectral signatures. Second, the successful identification of chemical tracers—particularly TCMTB—embedded in wet-blue leather confirmed that these tracers produce distinguishable spectral signals. This supports the use of spectroscopy for robust traceability. Finally, differences in model performance between grain and flesh sides, as well as between instruments, highlighted the impact of matrix variability on tracer detectability. These results underline the importance of matrix-specific calibration and instrument selection for accurate, scalable traceability solutions in industrial leather processing.

4. Conclusion

This study confirms the viability of Vis-NIR spectroscopy and hyperspectral imaging (HSI) as dual-purpose tools for enhancing sustainability in leather production. Two core objectives were achieved: (1) predicting microbial spoilage in raw bovine hides and (2) identifying chemical tracers in wet-blue leather.

PLSR models based on grain and flesh side spectra accurately predicted bacterial loads, demonstrating strong generalisability across storage temperatures and hide batches. Prediction maps visualised spoilage progression, supporting HSI's use as a decision-making tool in hide selection and sorting. Industrial adoption could reduce unnecessary chemical processing, conserve materials, and redirect spoiled hides for alternative use.

In parallel, preliminary classification efforts indicate that tracer-treated leather can be reliably distinguished from controls using Vis-NIR spectral features. Grain-side spectra, in particular, offer strong potential for supporting traceability verification. While specific model outcomes are reserved for future publication, early results suggest that compact spectrometers such as the Sagitto system may be suitable for in-field or supply chain applications.

Collectively, these findings support the industrial integration of Vis-NIR technologies for real-time quality control and traceability in leather production. Future work should explore tracer stability under long-term storage and refine microbial detection models through denser sampling. Broad adoption of these methods could enhance environmental stewardship, reduce waste, and align the leather industry with global sustainability standards.

5. Acknowledgements

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