



VIS–SWIR hyperspectral imaging for campaign-year verification and moisture screening in smoked paprika (*Capsicum annuum* L.)

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ABSTRACT

Smoked paprika from three production campaigns (2023–2025) was analysed by line-scan hyperspectral imaging (HSI) to assess campaign-year discrimination and screening of reference indices. Ninety-one commercial lots were scanned with two complementary cameras, Specim FX10 (400–1000 nm) and Specim FX17 (900–1700 nm). Spectra were preprocessed using scatter-correction and derivative-based methods, and principal component analysis was first used to identify informative preprocessing strategies. Supervised models were then developed under repeated nested cross-validation using partial least squares discriminant analysis (PLS-DA), support vector machines (SVMs), and partial least squares regression (PLSR). Both cameras achieved reproducible campaign-year discrimination, with balanced accuracies of 96–98%, and linear models performed comparably to radial basis function SVMs. Variable-importance profiles highlighted carotenoid-related bands in the visible region and O–H/C–H overtone regions in the SWIR. Reference measurements showed between-campaign variability in American Spice Trade Association (ASTA) colour indices, whereas moisture followed a clearer storage-related trend. Moisture prediction from FX17 spectra showed the strongest regression performance ($r = 0.926$; RMSE = 1.138), while ASTA D0, ASTA D3 and colour loss showed lower predictive performance. Overall, VIS–SWIR HSI provided a robust framework for campaign-year discrimination and rapid moisture screening in smoked paprika.

1. Introduction

Paprika, obtained from dried and milled fruits of *Capsicum annuum* L., is a globally traded spice whose commercial quality is largely determined by its chemical composition and its evolution during storage. Three compound families underpin sensory and market value: (i) carotenoids—particularly capsanthin and capsorubin—responsible for colour intensity; (ii) capsaicinoids, the source of pungency in hot varieties; and (iii) lipids, which solubilise pigments and influence oxidative stability (Arimboor et al., 2015; Barbero et al., 2016; Kostrzewa et al., 2022, 2023; Ponder et al., 2021; Wesolowska et al., 2011). In this context, *Pimentón de la Vera* (PDO), registered as a Protected Designation of Origin in the European Commission, 2007 (Commission Regulation (EC) No 982/2007), is distinguished by traditional smoke-drying using

holm and oak wood. Compared with hot-air drying, smoke-drying dehydrates the fruit more slowly and imparts phenolic volatiles (e.g., syringol and guaiacol), resulting in a characteristic smoky aroma (Barbosa et al., 2020; Cetó et al., 2018; Coletto et al., 2021). As a result, final quality reflects cultivar traits together with smoke-induced chemical transformations, and it may vary across production campaigns (i.e., harvest years). In practice, this variability, combined with the risk of lot mixing and mislabelling, motivates rapid, non-destructive approaches that can support routine verification at lot level.

After packaging, quality continues to evolve during storage. Carotenoids—the main determinants of paprika colour—are susceptible to oxidation and co-oxidation pathways that are often coupled to lipid oxidation (Arimboor et al., 2015; Kostrzewa et al., 2022; Pérez-Gálvez et al., 2003). Consistently, colour loss in paprika has frequently been

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described using first-order kinetics (Topuz, 2008). In parallel, the lipid fraction undergoes autoxidation via free-radical chain reactions (Pérez-Gálvez & Mínguez-Mosquera, 2004). The temperature dependence of these degradation routes follows Arrhenius-type behaviour (Topuz, 2008), highlighting that shelf life is governed by a network of reactions that is highly sensitive to temperature, oxygen availability, and light exposure (Kostrzewa et al., 2022). From a control perspective, these dynamics translate into a need for practical indicators that can be screened rapidly and repeatedly, enabling timely decisions on lot segregation and quality monitoring.

Quality assessment traditionally relies on reference methods. The American Spice Trade Association (ASTA) 20.1 spectrophotometric assay is an industry benchmark for colour, while CIE L*a*b* colourimetry provides objective chromatic coordinates (Arimboor et al., 2015; Kostrzewa et al., 2022; Topuz, 2008). For molecular specificity, high-performance liquid chromatography with diode-array detection (HPLC-DAD) quantifies individual carotenoids, and chromatographic fingerprints have been used for authenticity-related assessments (Cetó et al., 2018; Kostrzewa et al., 2023; Pérez-Gálvez et al., 2003; Sun et al., 2022). However, these techniques are destructive, relatively low-throughput, and solvent-intensive. Moreover, they provide bulk measurements that can mask within-lot heterogeneity, limiting their suitability for at-line or in-line control. This creates an operational gap for rapid, non-invasive screening methods that can capture both compositional information and spatial heterogeneity at lot level.

Hyperspectral imaging (HSI) integrates spatial and spectral information across the visible (VIS), near-infra-red (NIR), and short-wave infra-red (SWIR) ranges, and has shown strong performance in food authentication and quality control applications. VIS wavelengths are sensitive to pigment-related features, whereas SWIR captures O–H and C–H overtone/combination absorptions linked to moisture and matrix composition (Medina-García et al., 2025; Pu et al., 2023; Wu et al., 2026; Zhu et al., 2020). In spices, HSI and related spectroscopic-chemometric approaches have been applied to origin/authenticity assessment, adulteration detection, and prediction of quality indicators (Castell et al., 2024; Choi et al., 2022; Galvin-King et al., 2020; Samrat et al., 2022; Van Haute et al., 2023; Wang et al., 2022). Nevertheless, relatively few studies have exploited the full VIS–SWIR span (~400–1700 nm) across multiple production campaigns under rigorous internal validation and model selection—an industrially relevant scenario for smoked paprika, where rapid verification of declared campaign and monitoring of storage-related change can support routine control decisions. In this study, we use two complementary line-scan cameras (VIS–NIR and NIR–SWIR) to address this need.

The primary contribution is framed as reference-linked compositional screening anchored to routine indices (ASTA colour and gravimetric moisture), with campaign discrimination/verification presented as a downstream application of this compositional fingerprint. Accordingly, this work evaluates whether VIS–SWIR HSI enables reproducible screening of smoked paprika lots by production campaign, provides chemically interpretable wavelength neighbourhoods in the VIS (pigment-related) and SWIR (moisture/matrix-related) domains, and supports moisture prediction as a rapid quality indicator. We hypothesise that pigment-driven differences dominate in the VIS region, whereas moisture/matrix signals dominate in the SWIR, jointly enabling campaign discrimination. To test this, we (i) benchmark linear and non-linear classifiers under repeated nested cross-validation, (ii) map stable, chemically interpretable wavelength neighbourhoods across VIS and SWIR, and (iii) relate spectra to ASTA colour and moisture using partial least squares regression.

2. Materials and methods

2.1. Raw materials and sampling

Smoked paprika (*Capsicum annum* L.; PDO “Pimentón de la Vera”)

was sampled from three production campaigns—2023 (n = 44), 2024 (n = 17) and 2025 (n = 30)—for a total of n = 91 lots, where n denotes the number of sampled commercial lots. All products were kept in their original unopened retail packaging (metal tins or laminated bags) and stored at room temperature, protected from light and external humidity until analysis. All spectral acquisitions and reference measurements were performed in 2025 within a common measurement window. In this cross-sectional design, campaign year concurrently reflects inter-annual variability and elapsed time since production at the time of measurement. Campaign year was defined according to the commercial information stated on the retail packaging provided by the producers. In the context of this PDO, the declared campaign year (20XX) typically corresponds to peppers harvested and smoke-dried in the autumn of the previous year (20XX–1).

By label, product types were distributed as follows: 2023 (sweet 16; semi-sweet 17; spicy 11), 2024 (sweet 7; semi-sweet 1; spicy 9), 2025 (sweet 11; semi-sweet 12; spicy 7). Detailed sampling metadata (producer/company, town/province, packaging and net weight, lot IDs, sieving/particle size, storage history, days until measurement, and technical replicates) are provided in Table S1 (Supplementary Material).

2.2. Hyperspectral imaging and spectrum acquisition

2.2.1. Sample presentation

Three grams of smoked paprika powder were levelled in 6 cm diameter Petri dishes to obtain a flat, homogeneous measurement area. Dishes were labelled and the lid removed for scanning. Tungsten-halogen lamps were switched on for at least 15 min before acquisition to stabilise emission.

2.2.2. Instrumentation and acquisition

Line-scan hyperspectral image cubes were acquired with Specim FX10 (visible–near infra-red, 400–1000 nm) and Specim FX17 (near-/short-wave infra-red, 900–1700 nm) cameras (Specim, Oulu, Finland) using Specim Lumo software. The conveyor speed was 15 mm s^{−1}. Nominal settings were 39.51 Hz frame rate and 4.02 ms exposure for FX10, and 37.14 Hz and 2 ms for FX17 (binning = 1). For each sample and camera, white and dark frames were captured immediately before acquisition (“Run white”, “Run dark”) to enable reflectance calibration.

2.2.3. Radiometric calibration

Radiometric calibration and spectral export were performed with custom MATLAB scripts. Raw radiance cubes (*I*) were cropped to common spatial dimensions (*nrow*, *ncol*, *nb*) along with their corresponding white (*W*) and dark (*D*) references to ensure pixel alignment. Subsequently, raw radiance was converted to relative reflectance (*R*) on a per-band basis as:

$$R = \frac{(I - D)}{(W - D)} \quad (1)$$

Calibrated reflectance values were clipped to the range [0, 1]. Wavelengths were retrieved from the ENVI header metadata.

2.2.4. ROI-based spectrum extraction

For Region of Interest (ROI) placement, pseudo-red–green–blue (RGB) composites were displayed to aid visualization. A circular ROI with a fixed radius of 30 pixels (≈17.3 mm) was defined interactively near the dish centre. For each accepted ROI, the mean reflectance spectrum was computed by averaging all pixels within the circular mask. The workflow saved a PNG snapshot with ROI overlays and exported one Excel file per sample containing Sample, Year, and one column per wavelength with calibrated reflectance.

2.3. Spectral preprocessing and principal component analysis

Reflectance spectra were processed in MATLAB R2025a using a

standardised pipeline to reduce scatter, remove baseline drift, and enhance weak absorption features prior to modelling. Eleven preprocessing variants were evaluated: raw reflectance; mean centring; Standard Normal Variate (SNV); Multiplicative Scatter Correction (MSC); baseline correction (third-order polynomial); first-derivative (Savitzky–Golay); second derivative (Savitzky–Golay); SNV + first derivative; SNV + s derivative; MSC + first derivative; MSC + second derivative. Scatter effects were corrected with SNV and MSC, the latter implemented by regressing each spectrum against the batch mean (first order fit) and adjusting slope and intercept. Low-frequency baseline components were removed by subtracting a third-order polynomial fitted to the band-index axis. High-frequency features were emphasised with Savitzky–Golay (SG) derivatives using a second-order polynomial and an 11-point window; first- and second-order derivatives were evaluated. When combined, scatter correction preceded differentiation (e.g., SNV + first derivative, MSC + second derivative). For completeness, mean centring was examined as a standalone transform. To preserve alignment with wavelength labels after differentiation, the leading one (first derivative) or two (second derivative) bands were truncated. Identical SG parameters were used for FX10 and FX17 during this exploratory stage.

Principal component analysis (PCA) was computed on column-centred data for every preprocessed variant. PC1–PC2 score plots were inspected by production campaign (2023, 2024, 2025) to visualise structure, and class separability in the PC1–PC2 subspace was summarised using the mean silhouette coefficient. Potential score outliers were flagged using the Mahalanobis distance in the PC1–PC2 plane with a chi-square threshold ($\alpha = 0.05$; $df = 2$) for diagnostic purposes only; no samples were removed prior to supervised modelling to avoid optimistic bias and information leakage. No additional smoothing or wavelength trimming was applied before PCA beyond derivative-induced band loss; any later spectral masking or target-specific windows, when used, are described in the supervised modelling sections. All choices affecting model selection and performance estimation were deferred to the nested cross-validation framework to prevent information leakage from this exploratory phase.

2.4. Supervised classification

Supervised modelling was conducted in MATLAB R2025a under a repeated, stratified nested cross-validation scheme to separate model selection from generalisation assessment. For each camera (FX17 shown; FX10 analogous), preprocessed data matrices (Section 2.3) were loaded and class labels encoded the production campaign (2023, 2024, 2025). All spectra passed completeness checks. Three preprocessing variants—MSC + first derivative, SNV + first derivative, and first derivative (Savitzky–Golay)—were evaluated independently.

The outer loop used 10-fold stratified cross-validation with 10 repetitions; when required by the minority class size, the effective number of folds was reduced (k_{eff}). Stratification was applied exclusively by campaign year; secondary stratification by paprika type was not feasible due to sparse year $\times$ type cells (e.g., semi-sweet in 2024, $n = 2$; Table S1), and types were therefore allowed to distribute naturally within the year-stratified folds. Within each outer training set, an inner 5-fold stratified cross-validation governed all model-selection steps, including hyperparameter tuning and feature selection. Random seeds were fixed globally ($\text{rng}(42)$) and per repetition ($\text{rng}(1000 + \text{rep})$). The outer test fold remained untouched until final evaluation.

Model families included partial least squares discriminant analysis (PLS-DA), linear support vector machines (SVM), and radial basis function (RBF) kernel SVM implemented via one-vs-all error-correcting output codes (ECOC). For PLS-DA, the number of latent variables was selected in the inner loop over a grid up to 15 components. SVM hyperparameters were optimised in the inner loop using MATLAB's routine (linear: BoxConstraint; RBF: BoxConstraint and KernelScale; maximum 20 objective evaluations). Features were standardised for

SVM (z-score within each training split). A PCA $\rightarrow$ linear SVM baseline was also considered, selecting the number of principal components from {5, 10, 20, 40} in the inner loop.

Feature selection was embedded in the inner loop using Variable Importance in Projection (VIP) computed on training data. VIP thresholds (0.80, 1.00, 1.20), Top-K rules (20, 40), and a no-selection control were assessed, enforcing a minimum of 10 variables when required. Wavelength-selection stability was summarised as per-band selection frequency accumulated over outer folds and repetitions.

2.4.1. Evaluation

Class imbalance across campaigns (2023 $n = 44$; 2024 $n = 17$; 2025 $n = 30$) was handled without resampling or class weighting, relying on stratified partitioning and balanced accuracy as the primary endpoint. Performance was summarised on outer-test predictions. The primary endpoint was balanced accuracy (mean class-wise recall); overall accuracy was reported secondarily. Confusion matrices were aggregated across outer folds for the best pipeline per variant. Paired statistical tests (paired t -test and Wilcoxon signed-rank test) were conducted on per-fold balanced accuracies. Class priors matched empirical frequencies; no class weighting or resampling was applied.

2.5. Reference compositional indices: ASTA colour and moisture

2.5.1. American spice trade association (ASTA) colour index

Extractable colour was determined according to AOAC International Official Method 971.26 (AOAC International, Horwitz, 2002), incorporating the modifications described by Topuz et al. (2009). Briefly, 0.100 g of dried sample were mixed with 20 mL of acetone (100%), stirred for 15 min, and then kept in the dark at 25 °C for 3 h with intermittent agitation. The extract was centrifuged (4500 rpm, 8 min), and a 1 mL aliquot of the supernatant was diluted with 4 mL of acetone. Absorbance was read at 460 nm in a 10 mm standard glass cuvette using a Shimadzu UV–1800 spectrophotometer (acetone blank). ASTA units were computed as:

$$ASTA = \frac{A_{460} \times 16.4}{W} \quad (2)$$

where A_{460} is the absorbance of the acetone extract and W is the sample mass (g). The initial measurement is denoted ASTA (D_0).

To evaluate light stability, an accelerated UV exposure test was performed by spreading paprika samples in glass Petri dishes and irradiating them for 72 h with a UV-A fluorescent lamp at a fixed 50 cm distance in a closed chamber maintained at 25 °C. After exposure, colour was determined again by the ASTA method as for D_0 , and the resulting value was denoted ASTA (D_3). Colour loss and colour retention were calculated as:

$$\text{Colour loss (\%)} = 100 \times \left[1 - \frac{ASTA(D_3)}{ASTA(D_0)} \right] \quad (3)$$

$$\text{Colour retention (\%)} = 100 \times \frac{ASTA(D_3)}{ASTA(D_0)} \quad (4)$$

All measurements were performed in technical replicates and randomised across batches to minimise instrumental drift. This method has shown strong correlation with carotenoid concentration in paprika and is considered a reliable predictor of colour stability during storage (Pérez-Gálvez et al., 2004).

2.5.2. Moisture

Moisture content was determined using the gravimetric oven-drying method (Latimer, 2023). Precisely 1 g of finely ground sample were placed in a pre-dried, tared glass capsule, dried in a forced-air oven (J.P. Selecta, Spain) at 105 °C for 24 h, cooled in a desiccator to room temperature, and weighed. Moisture was calculated as:

$$\text{Moisture}(\%) = 100 \times \frac{(\text{initial weight} - \text{final weight})}{\text{initial weight}} \quad (5)$$

Analyses were run in technical replicates.

2.6. Regression modelling of reference indices

Partial least squares regression (PLSR) was used to model ASTA D0, ASTA D3, colour loss (%), and moisture (% wet basis) from hyperspectral predictors. Targets were paired to the spectroscopic range most relevant for each matrix: FX10 (400–1000 nm) for ASTA D0/D3, FX17 (900–1700 nm) for moisture, and fusion of FX10 and FX17 for colour loss. Fusion analyses used explicit matching by Sample_ID; unmatched samples were excluded.

Predictor matrices were assembled from the preprocessed groups described in Section 2.3. In addition to full-spectrum models, a priori spectral windows were evaluated per target based on expected sensitivity: ASTA D0 (450–520, 560–590, 620–720 nm), ASTA D3 (700–740 nm), colour loss (695–710, 500–560 nm), and moisture (980–1015, 1190–1230, 1420–1470, 1530–1550 nm). For each target, both Full and Window variants were tested.

Model selection and performance estimation followed a nested cross-validation protocol mirroring Section 2.4. The outer loop used K-fold cross-validation (K = 5), stratified by Year (2023, 2024, 2025); the inner loop used K = 5 to select the number of latent variables (LVs). To prevent leakage, median imputation (per band) and feature scaling (z-score) were computed within the training split and applied unchanged to validation/test partitions. Candidate LVs were explored up to 20 (capped at $\text{rank}(X_{\text{train}}) - 1$); inner-loop selection used the one-standard-error (1-SE) rule. Leave-one-year-out (LOYO) cross-validation was not used in this study (although available in the code).

Performance on outer-test predictions was summarised as root mean square error (RMSE), mean absolute error (MAE), R^2 , Pearson's r , and bias (mean predicted – observed). The best variant per target was identified by the lowest mean outer-fold RMSE.

2.7. Implementation details and outputs

All analyses were performed in MATLAB R2025a (MathWorks) with Statistics and Machine Learning Toolbox R2025a and Parallel Computing Toolbox R2025a on a Microsoft Windows 64-bit workstation (Intel® Core™ i7–9700KF @ 3.60 GHz, 8 cores; 32 GB RAM). Reproducibility was enforced with fixed randomisation: a global seed `rng(42, 'twister')` and repetition-specific seeds `rng(1000 + rep, 'twister')` for outer-loop partitions. Parallelisation used `parfor` with a local pool of up to 8 workers. All data-dependent transforms (z-score standardisation and median imputation) were fitted within the training split and applied unchanged to validation/test splits (Sections 2.4–2.6). Standard reports and figures corresponding to Sections 2.4–2.6 were generated, together with per-fold performance summaries. All MATLAB scripts have been permanently archived on Zenodo (10.5281/zenodo.17543067). All datasets underpinning the analyses are publicly available in Zenodo repositories; detailed DOIs are provided in the Data availability statement.

3. Results

3.1. Unsupervised analysis

Principal component analysis (PCA) was applied to the hyperspectral datasets acquired with the FX10 (VIS–NIR) and FX17 (NIR–SWIR) cameras, each evaluated under eleven preprocessing strategies (Tables 1 and 2). Across both systems, substantial variation was observed in the variance explained by the first two principal components and in the degree of inter-annual structure in score space. For FX10, PC1 accounted for 23.63% (MSC + second derivative, SNV + second derivative, and SG

Table 1

Summary of PCA and exploratory PLS-DA metrics for eleven preprocessing methods applied to FX10 spectra, including variance explained by PC1 and PC2, PLS-DA classification accuracy (%), number of outliers, and overall silhouette index.

Preprocessing	PC1 Var. (%)	PC2 Var. (%)	PLS-DA Acc. (%)	Outliers (n)	Silhouette index
MSC + 1st derivative	62.08	11.99	94.12	6	0.243
SNV + 1st derivative	61.92	12.24	94.12	6	0.239
1st derivative (SG)	64.69	12.58	97.70	4	0.173
Baseline (Poly)	66.79	23.77	79.31	4	0.009
SNV	80.79	8.69	80.68	3	−0.026
MSC (Corrected)	80.88	8.68	80.68	3	−0.026
MSC + 2nd derivative	23.63	17.91	96.59	3	−0.038
SNV + 2nd derivative	23.63	17.93	96.59	3	−0.039
2nd derivative (SG)	23.69	19.15	96.59	3	−0.064
Mean centring	87.19	9.13	82.35	6	−0.158
Raw reflectance	87.19	9.13	82.35	6	−0.158

Table 2

Summary of PCA and exploratory PLS-DA metrics for eleven preprocessing methods applied to FX17 spectra, including variance explained by PC1 and PC2, PLS-DA classification accuracy (%), number of outliers, and overall silhouette index.

Preprocessing	PC1 Var. (%)	PC2 Var. (%)	PLS-DA Acc. (%)	Outliers (n)	Silhouette index
SNV + 1st derivative	61.44	12.11	95.45	1	0.153
MSC + 1st derivative	61.28	12.35	95.45	1	0.153
1st derivative (SG)	64.40	12.57	94.32	3	0.136
Baseline (Poly)	66.60	23.79	81.82	6	−0.031
SNV	80.64	8.70	81.82	4	0.015
MSC (Corrected)	80.72	8.70	81.82	4	0.015
MSC + 2nd derivative	23.39	17.93	93.18	4	0.087
SNV + 2nd derivative	23.39	17.93	93.18	4	0.088
2nd derivative (SG)	23.45	19.18	93.18	4	0.090
Mean centring	86.92	9.13	81.82	6	−0.077
Raw reflectance	86.92	9.13	81.82	6	−0.077

second derivative) to 87.19% (mean centring and raw reflectance) of the variance, while PC2 ranged from 8.68% to 23.77%. For FX17, PC1 varied from 23.39% (MSC + second derivative, SNV + second derivative, and SG second derivative) to 86.92% (mean centring and raw reflectance), and PC2 from 8.70% to 23.79%.

Across both cameras, derivative-based preprocessing—particularly the first derivative, alone or combined with multiplicative scatter correction (MSC) or standard normal variate (SNV)—consistently yielded the highest silhouette indices and the lowest incidence of flagged score outliers. In FX10, the top three methods exhibited silhouette values above the overall median and tended to flag fewer outliers than most alternative approaches. A similar pattern was observed in FX17, where the same family of derivative-based methods dominated, providing the strongest unsupervised separation.

The performance gap between the best- and worst-ranked preprocessing strategies was more pronounced in FX10, with differences in silhouette index exceeding 0.30, compared with just over 0.20 in FX17. In both cameras, mean centring, baseline correction, SNV or MSC

without derivatives, and raw reflectance produced diffuse and overlapping clusters in the PCA score space, reflected in near-zero or negative silhouette values. Conversely, score plots for the best-performing methods (Figs. 1 and 2) showed compact and well-separated clusters for the 2025 campaign, with clear inter-annual boundaries and limited within-class dispersion, supporting the use of derivative-based preprocessing prior to supervised modelling.

3.2. Supervised classification – FX10 (VIS–NIR)

Based on the exploratory PCA analysis (Section 3.1), three preprocessing strategies were prioritised for FX10 spectra: MSC + first derivative, SNV + first derivative, and SG first derivative alone. These transformations consistently produced compact and well-separated clusters across campaign years, with high silhouette indices and low outlier incidence. The three preprocessings were therefore carried forward to the repeated nested cross-validation framework described in Section 2.4.

Across all three derivative-based preprocessing strategies, supervised models trained on FX10 spectra achieved consistently high performance. Differences between preprocessings were marginal, indicating that the VIS–NIR range contains robust discriminative information for campaign-year classification. PLS-DA and linear SVM yielded comparable results, whereas the non-linear SVM did not provide a systematic advantage. Notably, the PCA → linear SVM baseline achieved performance indistinguishable from the optimised full-dimensional models, suggesting that the campaign structure is largely preserved after dimensionality reduction and that linear decision boundaries are sufficient once representation is appropriately handled.

Among the tested models, the highest mean balanced accuracy was achieved by the PCA → linear SVM configuration under SNV + first derivative preprocessing. PLS-DA and linear SVM with VIP-based feature selection reached nearly identical values, indicating convergence of distinct modelling strategies towards a common performance ceiling (Table 3). Pairwise comparisons using the Wilcoxon signed-rank test did not reveal statistically significant differences among the top-performing models ($p > 0.05$), supporting the conclusion that performance remained stable across alternative pipelines. Accordingly, PCA → linear SVM with SNV + first derivative was retained as a representative model for confusion-matrix analysis.

Confusion patterns were highly consistent across the three derivative-based preprocessings: errors were rare, concentrated in the intermediate year, and approximately symmetric towards adjacent classes. The near-perfect, concordant diagonals indicate that decision boundaries in VIS–NIR space are robust to the specific derivative-based transformation and remain preserved after PCA projection. The SNV + first derivative variant showed a marginally stronger diagonal for the most recent class, consistent with its top mean balanced accuracy (Fig. 3).

VIP-based selection stability was high across all three preprocessings, with the SNV + first derivative profile consistently slightly above the MSC and SG traces. The curves moved in parallel, indicating that the inner-loop selector converged on highly similar wavelength subsets irrespective of preprocessing (Fig. 4A). The stability landscape exhibited clear spectral structure: maxima clustered in the blue–violet visible region, stability decreased through the green/blue-green, and then increased again towards the red and red-edge with recurrent peaks. Beyond the red-edge, profiles settled into a broad, moderately undulating plateau across the NIR, with a mild resurgence towards the short-wave end near the water overtone. These features were shared across preprocessings, confirming that frequently retained wavelengths occupy compact and recurrent spectral neighbourhoods (Fig. 4A).

The consensus panel corroborated these observations: the min–max envelope remained narrow across most of the spectrum and widened only around the visible troughs, while the mean profile preserved the same dominant peaks. The limited amplitude of the envelope indicates

sparse and reproducible selection across resampling folds and preprocessing variants, i.e., FX10 models repeatedly relied on a compact subset of VIS–NIR wavelengths (Fig. 4B).

3.3. Supervised classification – FX17 (NIR–SWIR)

Based on the PCA screening (Section 3.1), three derivative-based preprocessing variants were retained for FX17: MSC + first derivative, SNV + first derivative, and SG first derivative. These variants were evaluated under the same repeated nested cross-validation framework used for FX10 to ensure strict separation between model selection and generalisation assessment (Section 2.4).

Across the three derivative-based preprocessing strategies, supervised models trained on FX17 spectra achieved uniformly high performance, with minimal variability across algorithms and preprocessing variants (Table 4). Linear methods remained competitive with the best pipelines, and the non-linear SVM did not provide systematic gains over linear counterparts. Performance under the SG first derivative was marginally higher for the top configurations, indicating that NIR–SWIR discriminatory features are well captured under this transformation (Table 4).

The highest mean balanced accuracy was obtained under the SG first derivative, with PCA → linear SVM and PLS-DA (all variables) reaching effectively indistinguishable values (Table 4). Pairwise comparisons using the Wilcoxon signed-rank test did not reveal statistically significant differences among the top-performing models ($p > 0.05$), supporting the conclusion that performance remained stable across alternative modelling approaches (Paired_Tests worksheet). Accordingly, PCA → linear SVM with SG first derivative was retained as a representative model for confusion-matrix analysis.

Across the three derivative-based preprocessings, FX17 yielded near-perfect diagonals with only sparse off-diagonal entries. Residual errors were confined almost entirely to the intermediate year, with spill-over towards adjacent classes rather than long-range swaps. This error pattern was consistent across preprocessings: the SG variant showed a marginal gain for the intermediate class, coupled with a slight increase in leakage from the most recent year into its neighbour, leaving overall performance effectively equivalent across the three strategies (Fig. 5).

VIP-based selection stability in NIR–SWIR showed highly concordant selection-frequency profiles across the three preprocessing variants, with the SNV trace typically running slightly above the MSC and SG counterparts and only modest separations at a few local extrema (Fig. 6A). The profiles exhibited reproducible spectral organisation: a sharp high-stability zone in the short-wave water overtone window (~950–980 nm), attenuation towards the ~1.00–1.06 μm region, and recurrent shoulders within the C–H second-overtone/combination manifold (~1100–1160 nm and ~1200–1260 nm), followed by a depression around ~1.26–1.32 μm (Fig. 6A). Stability then increased steeply into a broad maximum spanning the strong water first-overtone region (~1400–1520 nm), with resolved local peaks within this band, before a transient decrease beyond ~1.52–1.58 μm and a renewed rise approaching the C–H first-overtone edge (~1660–1690 nm) (Fig. 6A).

The consensus panel confirmed these features at the aggregate level: the mean profile reproduced the same sequence of peaks and troughs, while the min–max envelope remained narrow over most wavelengths and widened primarily around the shoulder complexes (~1100–1160 nm and ~1200–1260 nm), across the apex of the water first-overtone plateau (~1400–1520 nm), and near the upper spectral bound (~1660–1690 nm) (Fig. 6B). Annotated maxima at ~1007, ~1139, ~1244, ~1427, ~1490, and ~1661 nm marked the most persistent selection hotspots across preprocessing strategies, with minor shifts in prominence but consistent ordering along the spectrum (Fig. 6B).

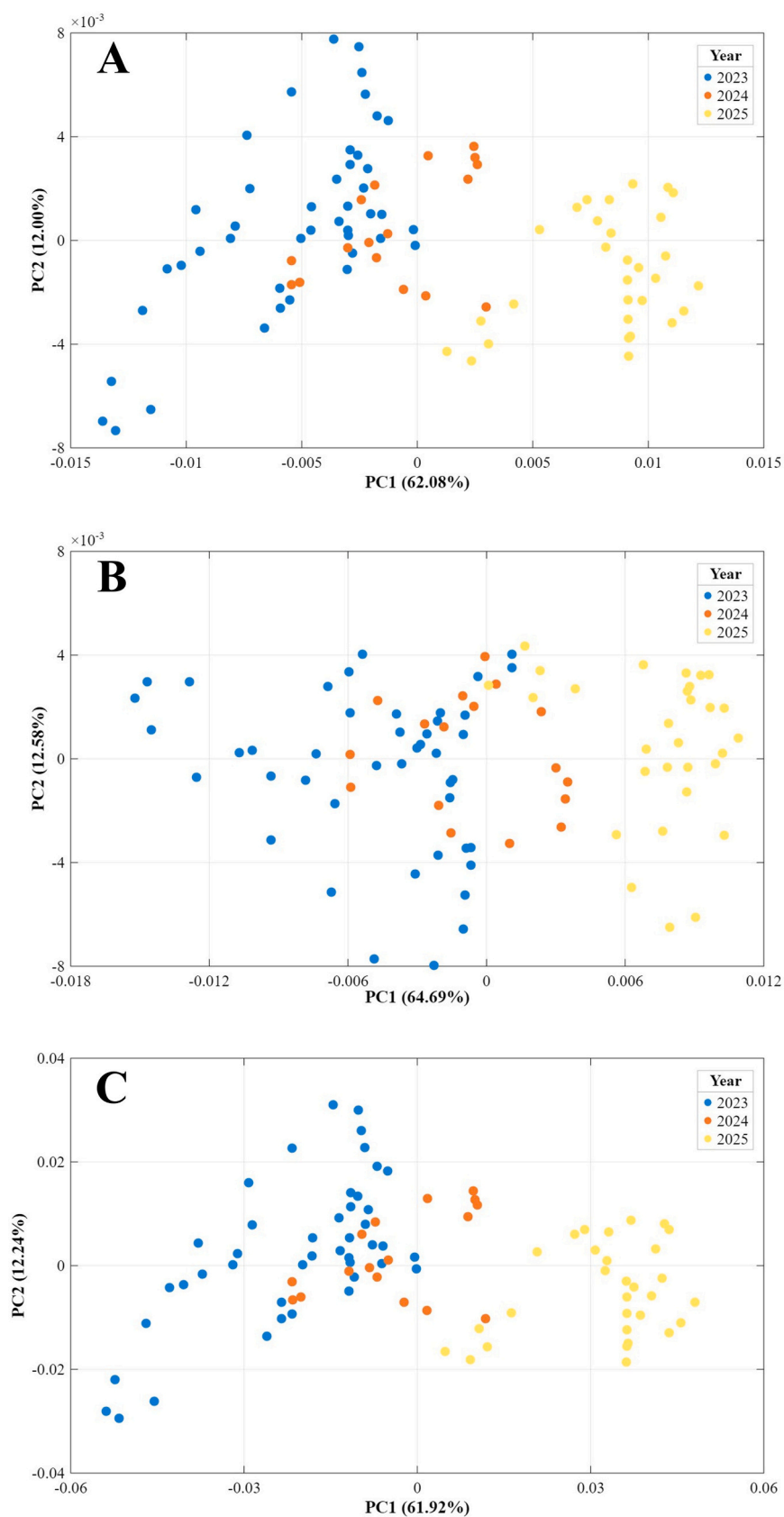


Fig. 1. PCA score plots for the three preprocessing methods with the highest silhouette indices in FX10: MSC + first derivative (A), SNV + first derivative (B), and SG first derivative (C).

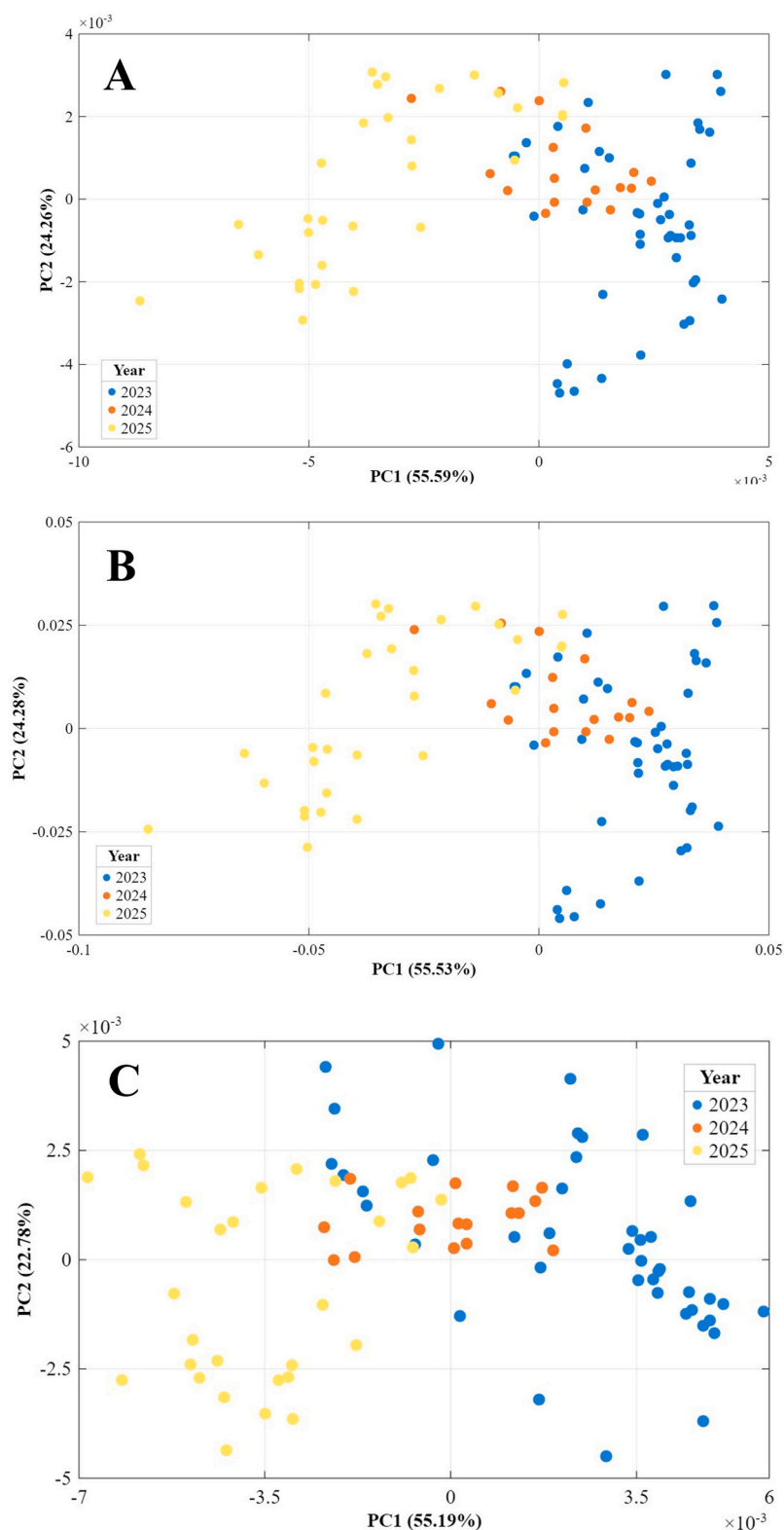


Fig. 2. PCA score plots for the three preprocessing methods with the highest silhouette indices in FX17: MSC + first derivative (A), SNV + first derivative (B), and SG first derivative (C).

3.4. Reference parameters (ASTA and moisture)

Descriptive statistics for the ASTA colour index (D0 and D3) and derived colour loss (%) were computed by campaign year (Table 5). Across campaigns, ASTA values showed marked inter-annual variability

both at baseline (D0) and after the accelerated light-stability assay (D3). In 2023, ASTA values before and after exposure remained relatively high, with limited mean colour loss. In 2024, ASTA D0 was lower and the decrease after exposure was more pronounced. In 2025, ASTA D0 recovered to higher values, but the post-exposure decline resulted in the

Table 3
Mean classification accuracy (Acc) and balanced accuracy (BalAcc) of six supervised models applied to FX10 spectra under three preprocessing strategies (MSC + first derivative, SNV + first derivative, and SG first derivative). Results were obtained from 100 outer folds of repeated nested cross-validation.

Model	MSC + 1st Derivative (Acc / BalAcc)	SNV + 1st Derivative (Acc / BalAcc)	SG 1st Derivative (Acc / BalAcc)
PLS-ALL	0.975 / 0.960	0.975 / 0.956	0.973 / 0.958
PLS-VIP	0.979 / 0.967	0.976 / 0.961	0.974 / 0.957
SVM-LIN-ALL	0.974 / 0.963	0.970 / 0.958	0.969 / 0.959
SVM-LIN-VIP	0.976 / 0.965	0.976 / 0.965	0.967 / 0.952
SVM-RBF-VIP	0.964 / 0.945	0.969 / 0.962	0.966 / 0.957
PCA + SVM- LIN	0.978 / 0.967	0.979 / 0.968	0.976 / 0.964

highest mean colour loss. Overall, these results indicate substantial between-campaign variability in both ASTA measurements and derived stability metrics, without a strictly monotonic pattern across campaign years (Table 5).

Moisture content also differed clearly between campaigns (Table 5). The oldest campaign (2023) exhibited substantially lower mean moisture, whereas 2024 and 2025 showed consistently higher values with comparatively limited dispersion. This separation is consistent with

Table 4
Mean classification accuracy (Acc) and balanced accuracy (BalAcc) of six supervised models applied to FX17 spectra under three preprocessing strategies (MSC + first derivative, SNV + first derivative, and SG first derivative). Results were obtained from 100 outer folds of repeated nested cross-validation.

Model	MSC + 1st Derivative (Acc / BalAcc)	SNV + 1st Derivative (Acc / BalAcc)	SG 1st Derivative (Acc / BalAcc)
PLS-ALL	0.969 / 0.961	0.975 / 0.969	0.977 / 0.975
PLS-VIP	0.975 / 0.968	0.971 / 0.964	0.970 / 0.965
SVM-LIN-ALL	0.978 / 0.972	0.977 / 0.970	0.976 / 0.970
SVM-LIN-VIP	0.977 / 0.971	0.976 / 0.970	0.977 / 0.971
SVM-RBF-VIP	0.966 / 0.959	0.967 / 0.960	0.975 / 0.969
PCA + SVM- LIN	0.973 / 0.967	0.971 / 0.969	0.981 / 0.975

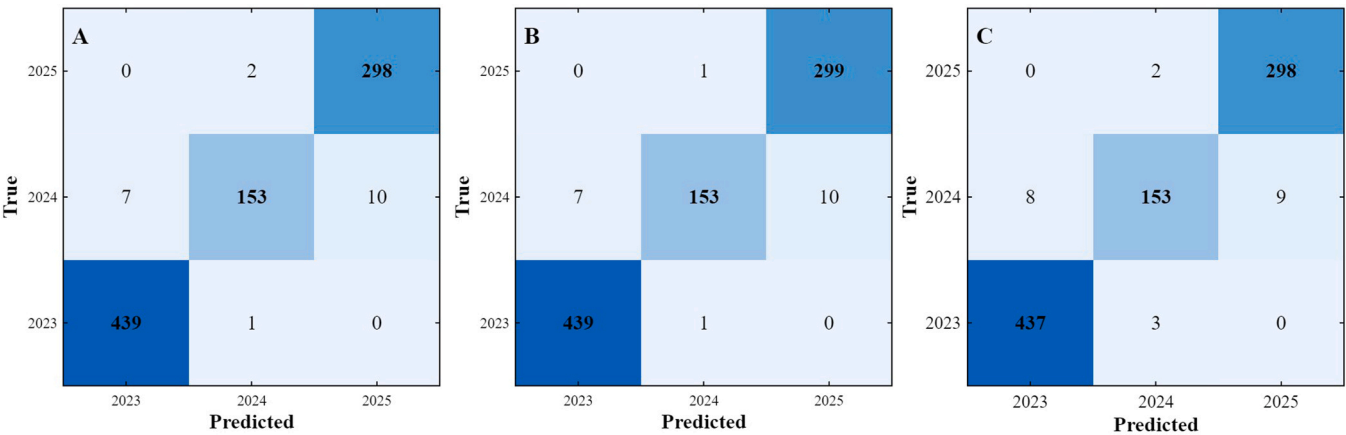


Fig. 3. Confusion matrices for FX10 (VIS-NIR) classification aggregated across 100 outer folds of repeated nested cross-validation (10 × 10 outer; 5-fold inner), using the PCA → linear SVM model. Panels: (A) MSC + first derivative, (B) SNV + first derivative, and (C) SG first derivative.

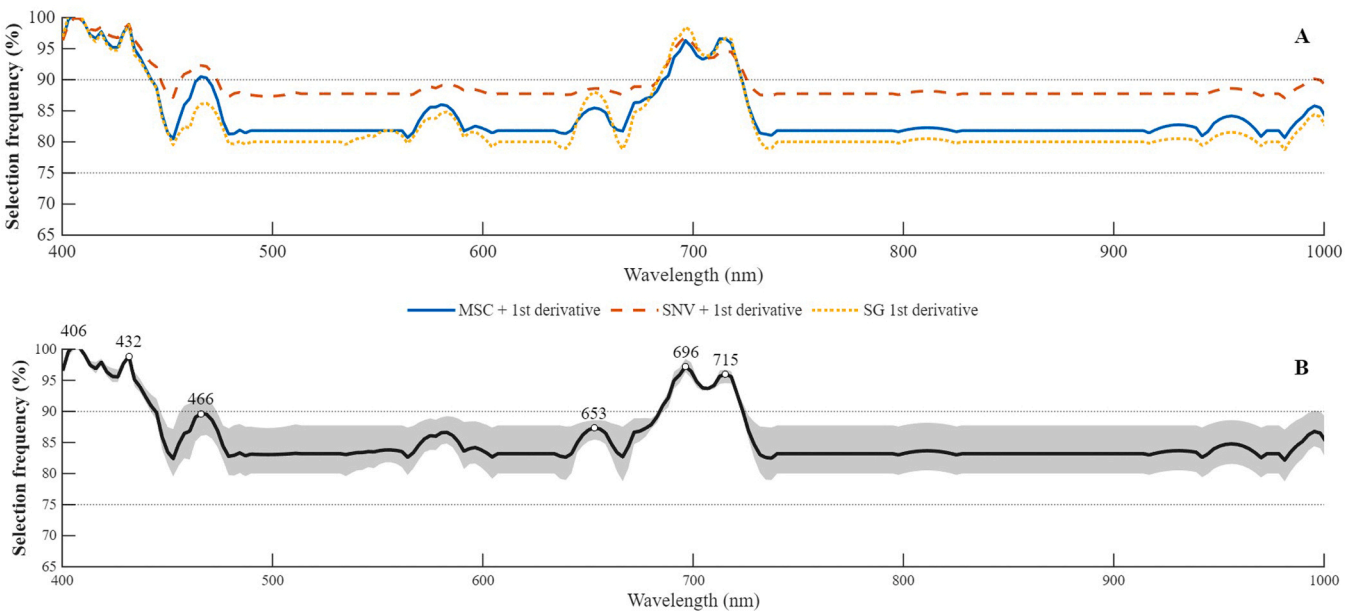


Fig. 4. VIP-based selection stability for FX10 (VIS-NIR). (A) Selection-frequency profiles across wavelength for three derivative-based preprocessings. (B) Consensus profile (solid line, mean; shaded band, min-max range across preprocessings) with annotated local maxima.

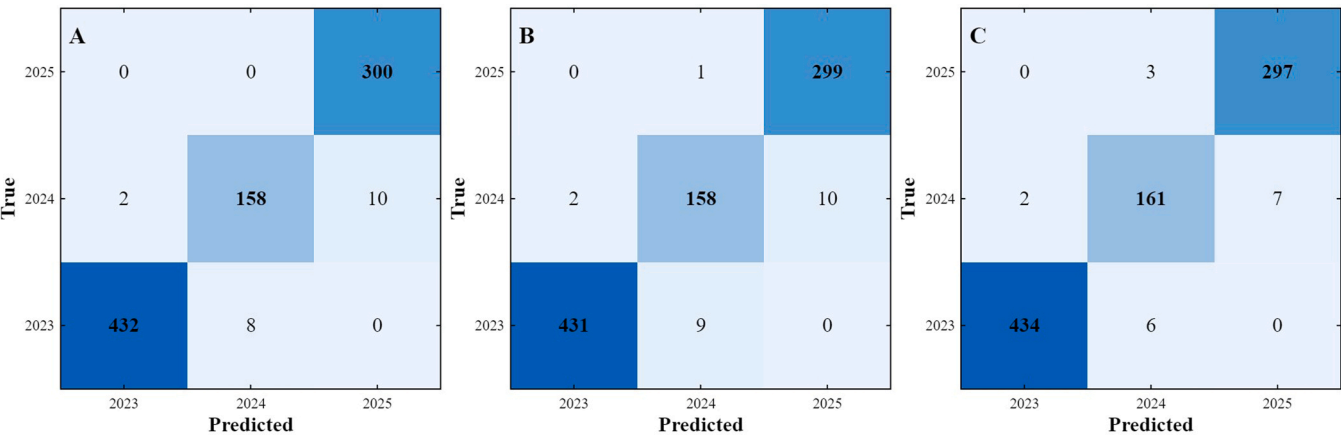


Fig. 5. Confusion matrices for FX17 (NIR-SWIR) aggregated across 100 outer folds of repeated nested cross-validation. Panels: (A) MSC + first derivative, (B) SNV + first derivative, and (C) SG first derivative.

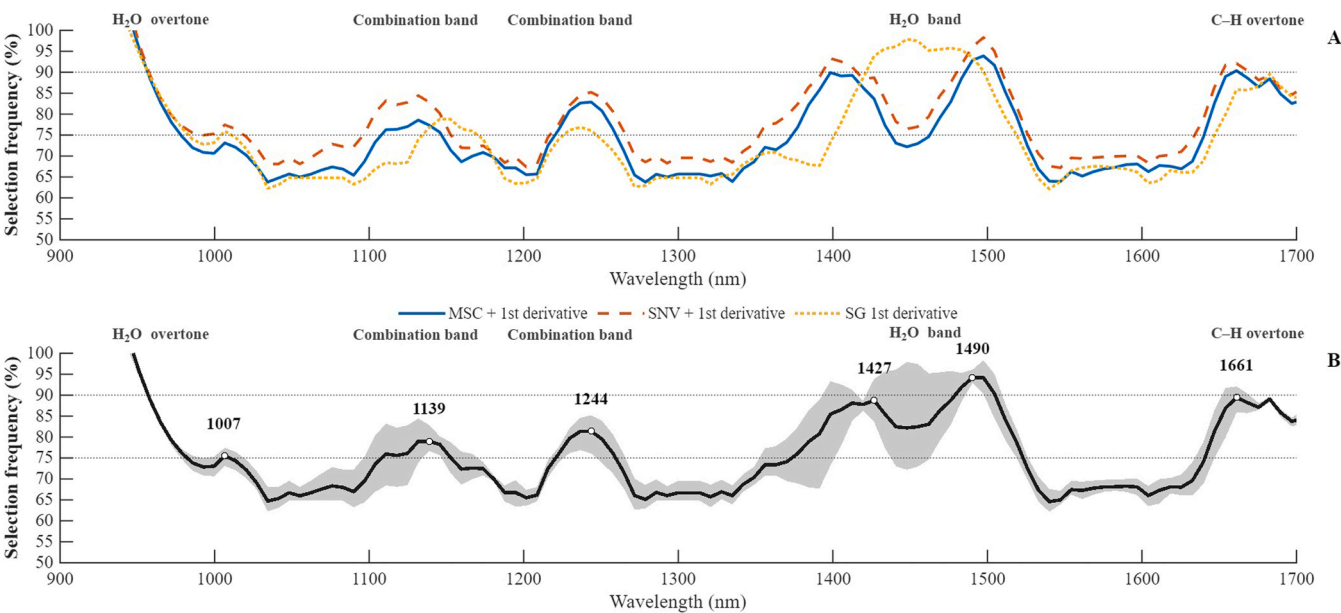


Fig. 6. VIP-based selection stability for FX17 (NIR-SWIR). (A) Selection-frequency profiles for MSC + first derivative, SNV + first derivative, and SG first derivative. (B) Consensus profile (solid line, mean across preprocessings) with min-max envelope (shaded band). Top annotations indicate canonical NIR-SWIR domains—H₂O overtone (~950–980 nm), C-H second overtones/combination bands (~1100–1260 nm), strong H₂O first overtone (~1400–1520 nm), and C-H first overtone (~1660–1690 nm); dashed horizontal lines mark the 75% and 90% selection thresholds.

Table 5
Descriptive statistics of ASTA indices (D0, D3), colour loss (%), and moisture (mean ± standard deviation) by campaign year.

Variable	2023 (n = 44)	2024 (n = 17)	2025 (n = 30)
ASTA D0	96.47 ± 17.49	74.47 ± 11.43	97.38 ± 18.65
ASTA D3	83.74 ± 17.42	57.70 ± 12.63	70.41 ± 16.19
Colour loss (%)	13.27 ± 7.61	23.02 ± 9.80	26.96 ± 13.49
Moisture (%)	3.79 ± 0.83	9.21 ± 0.83	9.54 ± 1.19

storage-related moisture changes over time and supports the use of moisture as a pragmatic screening attribute at lot level.

PLS regression models developed from FX17 spectra produced moisture estimates that agreed well with reference measurements under nested cross-validation (Fig. 7). Observed versus predicted values followed the identity line with limited dispersion, and residuals remained centred without obvious systematic trends. Model performance is summarised by RMSE and Pearson's *r* as reported in Fig. 7.

Additional PLS regression analyses were performed using ASTA D0, ASTA D3, and colour loss as reference variables. Compared with moisture, these models showed lower predictive performance, with correlation coefficients ranging from *r* = 0.48–0.67 and RMSE values between 10 and 16 units. Scatter plots indicated broad dispersion around the identity line, particularly at the extremes of the colour range. These complementary analyses are provided in the [Supplementary Material \(Fig. S1\)](#).

4. Discussion

4.1. Campaign-year discrimination and model parsimony

Across two complementary spectral ranges, hyperspectral imaging (HSI) enabled accurate and reproducible discrimination among smoked paprika campaign years (2023–2025), in line with the expanding evidence base for HSI in food quality, integrity and authenticity assessment (Choi et al., 2022; Monago-Maraña et al., 2022). Top pipelines achieved

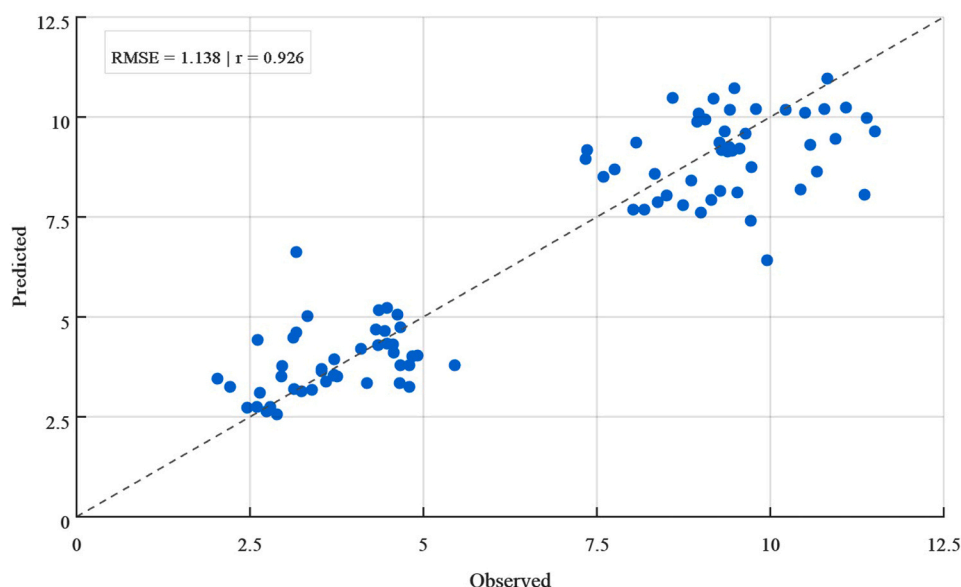


Fig. 7. Scatter plot of observed versus predicted moisture values obtained with PLS regression under nested cross-validation. Each point represents an individual sample; the dashed line indicates the 1:1 reference. RMSE, root mean square error; r , Pearson correlation coefficient.

balanced accuracies in the high 0.90 s for both VIS–NIR (FX10) and NIR–SWIR (FX17), and paired Wilcoxon comparisons indicated no meaningful performance separation among the leading approaches ($p > 0.05$). Notably, linear classifiers (PLS-DA, linear SVM) and PCA-reduced linear SVM performed comparably to a non-linear SVM with a RBF kernel, supporting parsimonious solutions in high-dimensional spectroscopy (Jiang et al., 2021; Medina-García et al., 2025; Van Haute et al., 2023; Wu et al., 2026). The decisive role of first-derivative preprocessing—shifting from weak or ambiguous structure in raw or scatter-only spectra to clearly separated classes post-derivative—reinforces the chemometric consensus that representation often dominates algorithm choice (Feng et al., 2019; Özdoğan et al., 2021; Su, 2020). Consistent with this, aggregated confusion matrices exhibited near-perfect diagonals for 2025 and 2023, with rare misclassifications largely confined to 2024. Notably, these 2024 errors manifested primarily as spill-over toward adjacent years rather than systematic attraction toward the 2023 majority class, and long-range swaps were rare, a pattern consistent with an intermediate spectral position. Nevertheless, the smaller 2024 class size remains a limitation and increasing its coverage would further refine decision boundaries and robustness.

4.2. Complementary domains and wavelength interpretation

Although FX10 and FX17 delivered comparable discrimination, they emphasised partially distinct chemical information. In the VIS–NIR range, VIP stability concentrated in blue–violet and red-edge regions commonly associated with carotenoid-related transitions (Falcioni et al., 2023; Gitelson et al., 2006; Matsuda et al., 2012). This is consistent with paprika colour loss being linked to carotenoid degradation and co-oxidation processes (Arimboor et al., 2015; Kostrzewa et al., 2022, 2023; Pérez-Gálvez & Mínguez-Mosquera, 2004; Topuz, 2008), and with the demonstrated utility of VIS spectroscopy for pigment-related attributes in complex matrices (Matsuda et al., 2012; Wang et al., 2022). In the NIR–SWIR range, recurrent VIP hotspots aligned with O–H and C–H overtone/combination regions, including the short-wave water overtone near ~ 970 nm, the strong first water overtone around ~ 1400 – 1520 nm, and C–H second/first overtone regions around ~ 1100 – 1260 nm and ~ 1660 – 1690 nm (Achata et al., 2015; Elmasry et al., 2012; Falcioni et al., 2023; Galindo-Prieto et al., 2021; Van Haute et al., 2023). The reproducible convergence of VIP profiles to compact wavelength

neighbourhoods across resampling and preprocessing constitutes an internal-consistency argument for interpretability and potential portability, while recognising that VIP reflects model importance under collinearity rather than mechanistic causality (Galindo-Prieto et al., 2021; Samrat et al., 2022).

4.3. Reference indices and regression performance

Reference measurements contextualised the multivariate patterns. ASTA indices varied markedly between campaigns, with lower values and greater loss in 2024 compared with 2023 and 2025, whereas moisture content followed a more coherent between-campaign pattern (Table 5). In regression, moisture PLSR achieved strong agreement with reference values. In this lipid-rich powdered matrix, this performance is not attributed solely to isolated O–H water absorption. Consistently, VIP profiles retained the dominant O–H region (~ 1400 – 1520 nm) together with C–H regions (e.g., ~ 1100 – 1260 nm and ~ 1660 – 1690 nm), supporting the interpretation that PLSR exploits multivariate covariance between moisture and matrix/lipid-related features (a ‘matrix-to-water’ context) to compensate for band overlap and scattering effects (Elmasry et al., 2012; Xu et al., 2015; Galvin-King et al., 2020; Crichton et al., 2018). By contrast, PLSR models for ASTA D0/D3 and colour loss were weaker ($r = 0.48$ – 0.67), with larger dispersion at the extremes (Fig. S1). This apparent mismatch between strong campaign discrimination and weak ASTA regression is consistent with a fundamental difference in measurement principles. HSI captures diffuse reflectance from the intact powder, where pigment-related regions are modulated by particle scattering/packing and pigment–matrix interactions, whereas ASTA reflects a solvent-extract colour index. Consequently, pigment-sensitive spectral regions can be highly discriminatory for campaign identity while remaining only weakly (and potentially nonlinearly) related to ASTA under linear PLSR, yielding the observed dispersion. Taken together, these results suggest that campaign-to-campaign colour variability may be driven predominantly by agro-climatic and processing factors (rather than a simple monotonic “time-since-processing” effect), whereas moisture differences are more amenable to modelling as a pragmatic screening attribute at lot level (Topuz, 2008; Kostrzewa et al., 2022). However, campaign year is collinear with elapsed storage time in this cross-sectional dataset (Section 2.1), and the present models should therefore be interpreted as verifying the declared campaign identity at the time of inspection, rather than isolating production effects from

post-production ageing. Longitudinal designs tracking multiple campaigns across storage time will be required to decouple baseline agro-climatic/processing effects from ageing dynamics.

4.4. Validation rigour and methodological considerations

The modelling strategy was designed to minimise selection bias and information leakage, recurrent issues in applied machine learning for spectroscopy and hyperspectral data analysis (Medina-García et al., 2025; Zhang et al., 2023). Model selection (inner CV) and generalisation assessment (outer CV) were strictly separated, and VIP-based feature selection was embedded within the inner loop, avoiding optimistic bias from whole-dataset filtering (Galindo-Prieto et al., 2021; Zhang et al., 2023). These elements align with best-practice internal validation when external cohorts are not yet available (Galvin-King et al., 2020). From a deployment perspective, the equivalence of linear and non-linear models further supports robust, transparent pipelines with lower implementation burden (Van Haute et al., 2023; Wu et al., 2026).

4.5. Practical implications, limitations and future work

For industrial quality control, either VIS–NIR or NIR–SWIR could underpin rapid, non-destructive verification of campaign year, with sensor choice guided by integration constraints, cost and target chemistry: VIS–NIR aligns with pigment/colour-related monitoring (including schemes linked to ASTA), whereas NIR–SWIR is particularly informative for moisture- and matrix-related attributes relevant to shelf-life management and oxidative deterioration risk (Özdoğan et al., 2021; Wu et al., 2026; Zhu et al., 2020). The narrow, stable VIP hotspots support band-reduced multispectral prototypes using a small number of filters centred on informative regions, reducing hardware and computational overhead while preserving performance (Van Haute et al., 2023; Wang et al., 2022; Wu et al., 2026).

Limitations include the single-source, three-campaign dataset and the lack of external validation across producers, cultivars, origins and additional campaigns (domain shift). The trained models and VIP-derived wavelength patterns are matrix- and dataset-dependent and should not be transferred ‘as is’ to other smoked paprika systems or GI products. However, the VIS–SWIR workflow is transferable as a methodology provided a representative baseline is acquired for the target matrix, followed by retraining and external validation across producers and campaigns. Extension to adulteration or blending would require dedicated mixture datasets and independent validation. Uncontrolled factors (e.g., particle size/packing, packaging material, ambient humidity and baseline moisture) may contribute to SWIR water-band behaviour. Although packaging (metal tins vs laminated bags) was not perfectly balanced across campaigns, both formats were represented in each campaign (2023: 32 tins/12 bags; 2024: 14/3; 2025: 21/9; Table S1), and packaging-related effects are therefore expected to contribute mainly to within-campaign variance. Residual confounding cannot be excluded and should be addressed in future studies using balanced/controlled packaging distributions and/or packaging-stratified analyses. Instrument drift/cross-unit transferability were not assessed. Finally, modelling targeted discrete campaign classes rather than continuous storage time, and VIP stability should not be over-interpreted mechanistically under collinearity. Priorities for future work therefore include external multi-producer validation, calibration transfer and drift monitoring, and band reduction guided by VIP consensus. Fusion of selected VIS and SWIR bands may further enhance robustness by capturing both pigment- and matrix-related pathways, and extension to additional reference indices (e.g., peroxide value) would strengthen alignment with routine specifications (Van Haute et al., 2023; Wu et al., 2026). Development of multi-index or multi-output prediction models is also a plausible next step, but their robust development will require larger and more diverse datasets together with independent external validation, especially given that

predictive performance in the present study was clearly stronger for moisture than for ASTA D0, ASTA D3, and colour loss.

5. Conclusions

This study demonstrates that line-scan VIS–SWIR hyperspectral imaging (HSI) provides a reference-linked compositional fingerprint of smoked paprika against routine indices (ASTA colour and moisture), while enabling reliable campaign-year classification (2023–2025) under rigorous repeated nested cross-validation. Across cameras, parsimonious linear pipelines (PLS-DA and linear SVM, with embedded VIP-based selection) matched the performance of non-linear kernels, supporting models that are easier to interpret and potentially more straightforward to implement after external validation. Stable, compact wavelength neighbourhoods were repeatedly selected in both spectral ranges, indicating reproducible spectral structure relevant to campaign discrimination.

Descriptive statistics for ASTA indices (D0, D3) and derived colour loss showed substantial inter-annual variability, consistent with agro-climatic and processing influences rather than a simple monotonic “time-since-processing” effect on colour. By contrast, moisture exhibited a clear and predictable pattern across campaign years, and PLS regression from SWIR spectra yielded accurate estimates under nested cross-validation, supporting HSI as a practical non-destructive proxy for residual water at lot level.

From a compositional quality-control perspective, either camera could underpin rapid screening for campaign-year verification, while SWIR is particularly suited to routine moisture monitoring. Accordingly, sensor choice can be guided by cost and target chemistry: VIS–NIR aligns with pigment/colour-related control, whereas NIR–SWIR is more informative for moisture- and matrix-related attributes. Key next steps include external validation across producers and campaigns, calibration transfer and drift monitoring, and band-reduced multispectral implementations that retain the stable informative regions identified here.

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CRedit authorship contribution statement

Santiago Ruiz-Moyano: Supervision, Resources. **Rocío Velázquez:** Investigation. **Mercedes Aranda:** Investigation, Data curation. **Córdoba María de Guía:** Investigation, Funding acquisition. **Jesús Alonso:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Emilio Aranda:** Investigation. **Alberto Martín:** Supervision, Project administration, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Gemini to enhance language clarity and readability. Additionally, SciSpace was utilised as a bibliographic source, and Scite was employed to assess the quality and reliability of the cited articles. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.jfca.2026.109097](https://doi.org/10.1016/j.jfca.2026.109097).

Data availability

All data and code supporting the findings of this study are publicly available in Zenodo (DOI: 10.5281/zenodo.17543067).

References

- Achata, E., Esquerre, C., O'Donnell, C., Gowen, A., 2015. A study on the application of near infrared hyperspectral chemical imaging for monitoring moisture content and water activity in low moisture systems. *Molecules* 20, 2611–2621. <https://doi.org/10.3390/molecules20022611>.
- AOAC International, 2002. In: Horwitz, W. (Ed.), *Official Methods of Analysis of AOAC International*, 17th ed. AOAC International, Gaithersburg, MD, USA. Official Method 971.26.
- Arimboor, R., Natarajan, R.B., Menon, K.R., Chandrasekhar, L.P., Moorkoth, V., 2015. Red pepper (*Capsicum annuum*) carotenoids as a source of natural food colors: analysis and stability—a review. *J. Food Sci. Technol.* 52, 1258–1271. <https://doi.org/10.1007/s13197-014-1260-7>.
- Barbero, G.F., Liadzi, A., Azaroual, L., Palma, M., Barroso, C.G., 2016. Capsaicinoid contents in peppers and pepper-related spicy foods. *Int. J. Food Prop.* 19, 485–493. <https://doi.org/10.1080/10942912.2014.968468>.
- Barbosa, S., Saurina, J., Puignou, L., Núñez, O., 2020. Classification and authentication of paprika by UHPLC-HRMS fingerprinting and multivariate calibration methods (PCA and PLS-DA). *Foods* 9, 486. <https://doi.org/10.3390/foods9040486>.
- Castell, A., Arroyo-Manzanares, N., López-García, I., Zapata, F., Viñas, P., 2024. Authentication strategy for paprika analysis according to geographical origin and study of adulteration using near infrared spectroscopy and chemometric approaches. *Food Control* 161, 110397. <https://doi.org/10.1016/j.foodcont.2024.110397>.
- Cetó, X., Serrano, N., Aragón, M., Gámez, A., Esteban, M., Díaz-Cruz, J.M., Núñez, O., 2018. Determination of HPLC-UV fingerprints of Spanish paprika (*Capsicum annuum* L.) for its classification by linear discriminant analysis. *Sensors* 18, 4479. <https://doi.org/10.3390/s18124479>.
- Choi, J.-Y., Cho, J.-S., Park, K.J., Choi, J.H., Lim, J.H., 2022. Effect of moisture content difference on the analysis of quality attributes of red pepper (*Capsicum annuum* L.) powder using a hyperspectral system. *Foods* 11, 4086. <https://doi.org/10.3390/foods11244086>.
- Coletto, J.M., Martín, A., Horrillo, A., Mesías, F.J., Velázquez, R., 2021. An approach to the consumption of smoked paprika in Spain and its impact on the intake of polycyclic aromatic hydrocarbons. *Foods* 10, 973. <https://doi.org/10.3390/foods10050973>.
- Crichton, S., Shrestha, L., Hurlbert, A., Sturm, B., 2018. Use of hyperspectral imaging for the prediction of moisture content and chromaticity of raw and pretreated apple slices during convection drying. *Dry. Technol.* 36, 804–816. <https://doi.org/10.1080/07373937.2017.1356847>.
- Elmasry, G., Kamruzzaman, M., Sun, D.-W., Allen, P., 2012. Principles and applications of hyperspectral imaging in quality evaluation of agro-food products: a review. *Crit. Rev. Food Sci. Nutr.* 52, 999–1023. <https://doi.org/10.1080/10408398.2010.543495>.
- European Commission, 2007. Commission Regulation (EC) No 982/2007 of 21 August 2007 registering certain names in the Register of protected designations of origin and protected geographical indications. *Official Journal of the European Union*, L 217, pp. 22–23.
- Falcioni, R., Antunes, W.C., Demattè, J.A.M., Nanni, M.R., 2023. A novel method for estimating chlorophyll and carotenoid concentrations in leaves: a two hyperspectral sensor approach. *Sensors* 23, 3843. <https://doi.org/10.3390/s23083843>.
- Feng, L., Zhu, S., Liu, F., He, Y., Bao, Y., Zhang, C., 2019. Hyperspectral imaging for seed quality and safety inspection: a review. *Plant Methods* 15, 91. <https://doi.org/10.1186/s13007-019-0476-y>.
- Galindo-Prieto, B., Geladi, P., Trygg, J., 2021. Multiblock variable influence on orthogonal projections (MB-VIOP) for enhanced interpretation of total, global, local and unique variations in OnPLS models. *BMC Bioinforma.* 22, 176. <https://doi.org/10.1186/s12859-021-04015-9>.
- Galvin-King, P., Haughey, S.A., Elliott, C.T., 2020. The detection of substitution adulteration of paprika with spent paprika by the application of molecular spectroscopy tools. *Foods* 9, 944. <https://doi.org/10.3390/foods9070944>.
- Gitelson, A.A., Keydan, G.P., Merzlyak, M.N., 2006. Three-band model for noninvasive estimation of chlorophyll, carotenoids, and anthocyanin contents in higher plant leaves. *Geophys. Res. Lett.* 33, L11402. <https://doi.org/10.1029/2006GL026457>.
- Jiang, H., Yang, Y., Shi, M., 2021. Chemometrics in tandem with hyperspectral imaging for detecting authentication of raw and cooked mutton rolls. *Foods* 10, 2127. <https://doi.org/10.3390/foods10092127>.
- Kostrzewa, D., Dobrzyńska-Inger, A., Mazurek, B., Kostrzewa, M., 2022. Pilot-scale optimization of supercritical CO₂ extraction of dry paprika *Capsicum annuum*: influence of operational conditions and storage on extract composition. *Molecules* 27, 2090. <https://doi.org/10.3390/molecules27072090>.
- Kostrzewa, D., Mazurek, B., Kostrzewa, M., Jóźwik, E., 2023. Carotenoids and fatty acids obtained from paprika *Capsicum annuum* by supercritical carbon dioxide and ethanol as co-extractant. *Molecules* 28, 5438. <https://doi.org/10.3390/molecules28145438>.
- Latimer Jr, G.W. (Ed.), 2023. *Official Methods of analysis of AOAC INTERNATIONAL*. Oxford University Press. <https://doi.org/10.1093/9780197610145.003.1381>.
- Matsuda, O., Tanaka, A., Fujita, T., Iba, K., 2012. Hyperspectral imaging techniques for rapid identification of *Arabidopsis* mutants with altered leaf pigment status. *Plant Cell Physiol.* 53, 1154–1170. <https://doi.org/10.1093/pcp/pcs043>.
- Medina-García, M., Amigo, J.M., Martínez-Domingo, M.A., Valero, E.M., Jiménez-Carvelo, A.M., 2025. Strategies for analysing hyperspectral imaging data for food quality and safety issues: a critical review of the last 5 years. *Microchem. J.* 214, 113994. <https://doi.org/10.1016/j.microc.2025.113994>.
- Monago-Maraña, O., Durán-Merás, I., Muñoz De La Peña, A., Galeano-Díaz, T., 2022. Analytical techniques and chemometrics approaches in authenticating and identifying adulteration of paprika powder using fingerprints: a review. *Microchem. J.* 178, 107382. <https://doi.org/10.1016/j.microc.2022.107382>.
- Özdoğan, G., Lin, X., Sun, D.-W., 2021. Rapid and noninvasive sensory analyses of food products by hyperspectral imaging: recent application developments. *Trends Food Sci. & Technol.* 111, 151–165. <https://doi.org/10.1016/j.tifs.2021.02.044>.
- Pérez-Gálvez, A., Martín, H.D., Sies, H., Stahl, W., 2003. Incorporation of carotenoids from paprika oleoresin into human chylomicrons. *Br. J. Nutr.* 89, 787–793. <https://doi.org/10.1079/BJN2003842>.
- Pérez-Gálvez, A., Mínguez-Mosquera, M.I., 2004. Degradation, under non-oxygen-mediated autooxidation, of carotenoid profile present in paprika oleoresins with lipid substrates of different fatty acid composition. *J. Agric. Food Chem.* 52, 632–637. <https://doi.org/10.1021/jf0351063>.
- Pérez-Gálvez, A., Mínguez-Mosquera, M.I., Garrido-Fernández, J., Lozano-Ruiz, M.M., Montero-de-Espinosa, V., 2004. Correlation between ASTA units–carotenoid concentration in paprika: Prediction of color stability during storage. *Grasas Y Aceites* 55, 213–218. <https://doi.org/10.3989/gya.2004.v55.i3.168>.
- Ponder, A., Kulik, K., Hallmann, E., 2021. Occurrence and determination of carotenoids and polyphenols in different paprika powders from organic and conventional production. *Molecules* 26, 2980. <https://doi.org/10.3390/molecules26102980>.
- Pu, H., Yu, J., Sun, D.-W., Wei, Q., Wang, Z., 2023. Feature construction methods for processing and analysing spectral images and their applications in food quality inspection. *Trends Food Sci. & Technol.* 138, 726–737. <https://doi.org/10.1016/j.tifs.2023.06.036>.
- Samrat, N.H., Johnson, J.B., White, S., Naiker, M., Brown, P., 2022. A rapid non-destructive hyperspectral imaging data model for the prediction of pungent constituents in dried ginger. *Foods* 11, 649. <https://doi.org/10.3390/foods11050649>.
- Su, W.-H., 2020. Advanced machine learning in point spectroscopy, RGB- and hyperspectral-imaging for automatic discriminations of crops and weeds: a review. *Smart Cities* 3, 767–792. <https://doi.org/10.3390/smartcities3030039>.
- Sun, X., Zhang, M., Wang, P., Chen, J., Yang, S., Luo, P., Gao, X., 2022. Detection and quantitation of adulterated paprika samples using second-order HPLC-FLD fingerprints and chemometrics. *Foods* 11, 2376. <https://doi.org/10.3390/foods11152376>.
- Topuz, A., 2008. A novel approach for color degradation kinetics of paprika as a function of water activity. *LWT Food Sci. Technol.* 41, 1672–1677. <https://doi.org/10.1016/j.lwt.2007.10.004>.
- Topuz, A., Feng, H., Kushad, M., 2009. The effect of drying method and storage on color characteristics of paprika. *LWT - Food Sci. Technol.* 42, 1667–1673. <https://doi.org/10.1016/j.lwt.2009.05.014>.
- Van Haute, S., Nikkha, A., Malavi, D., Kiani, S., 2023. Prediction of essential oil content in spearmint (*Mentha spicata*) via near-infrared hyperspectral imaging and chemometrics. *Sci. Rep.* 13, 4261. <https://doi.org/10.1038/s41598-023-31517-8>.
- Wang, Y., Yang, J., Yu, S., Fu, H., He, S., Yang, B., Nan, T., Yuan, Y., Huang, L., 2022. Prediction of chemical indicators for quality of *Zanthoxylum* spices from multi-regions using hyperspectral imaging combined with chemometrics. *Front. Sustain. Food Syst.* 6, 1036892. <https://doi.org/10.3389/fsufs.2022.1036892>.
- Wesołowska, A., Jadcak, D., Grzeszczuk, M., 2011. Chemical composition of the pepper fruit extracts of hot cultivars *Capsicum annuum* L. *Acta Sci. Pol. Hortorum Cultus* 10, 171–184. (<https://czasopisma.up.lublin.pl/asphc/article/view/3190/2226>).
- Wu, S., Huang, L., Huang, R., 2026. Review of advances in hyper-spectral imaging-based non-destructive testing methods in food application. *J. Food Compos. Anal.* 150, 108860. <https://doi.org/10.1016/j.jfca.2026.108860>.
- Xu, J., Riccioli, C., Sun, D., 2015. An overview on nondestructive spectroscopic techniques for lipid and lipid oxidation analysis in fish and fish products. *Compr. Rev. Food Sci. Food Saf.* 14, 466–477. <https://doi.org/10.1111/1541-4337.12138>.
- Zhang, X., Yan, J., Tian, J., Li, W., Gu, X., Tian, Q., 2023. Objective evaluation-based efficient learning framework for hyperspectral image classification. *GIScience & Remote Sens.* 60, 2225273. <https://doi.org/10.1080/15481603.2023.2225273>.
- Zhu, M., Huang, D., Hu, X., Tong, W., Han, B., Tian, J., Luo, H., 2020. Application of hyperspectral technology in detection of agricultural products and food: a review. *Food Sci. & Nutr.* 8, 5206–5214. <https://doi.org/10.1002/fsn3.1852>.