

Review

From Farm to Fork: Integrating Smart Farming Data with Isotopic and Spectroscopic Analysis for Food Authentication and Traceability

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Abstract

Ensuring food authenticity, traceability, and quality has become a critical challenge in increasingly complex and globalized food supply chains. Conventional post-harvest analytical approaches, while powerful, often operate in isolation and fail to fully capture the influence of pre-harvest conditions on food composition. In parallel, the emergence of smart farming technologies has enabled the collection of high-resolution environmental and agronomic data, offering new opportunities to establish baseline signatures linked to geographical origin and production practices. This review explores the integration of pre-harvest data from precision agriculture with advanced post-harvest analytical techniques, focusing on spectroscopic and isotopic methods for food authentication. Recent advances in vibrational spectroscopy, including near- and mid-infrared, Fourier-transform infrared, and Raman techniques, alongside complementary methods such as nuclear magnetic resonance and fluorescence spectroscopy, have enabled rapid and non-destructive food fingerprinting. In parallel, isotope ratio mass spectrometry and compound-specific isotope analysis provide robust markers of origin, climate conditions, and agricultural inputs through the analysis of stable isotopes of carbon, hydrogen, oxygen, nitrogen, and sulfur. The combination of these analytical approaches with chemometric and machine learning tools facilitates the extraction of meaningful patterns from complex datasets. A central focus of this review is the development of integrated farm-to-fork frameworks that use multi-source data, including field sensor technologies, spectral fingerprints, and isotopic signatures, to enhance traceability and authentication. Applications across a wide range of food systems, including edible oils, beverages, plant-based products, and animal-derived foods, are critically evaluated to highlight the strengths and limitations of current methodologies. Key challenges related to data standardization, system interoperability, cost, portability, miniaturization and regulatory acceptance are discussed, alongside emerging solutions such as artificial intelligence-driven models, digital twins, and blockchain-enabled traceability systems. The review underscores a paradigm shift from reactive testing toward predictive and real-time food authentication systems, driven by the convergence of smart agriculture and advanced analytical chemistry. This integrated approach has the potential to significantly enhance transparency, trust, and sustainability in the global food system.



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1. Introduction

Food authentication and traceability are entering a new phase in which analytical accuracy alone is no longer sufficient to guarantee reliable origin verification across complex agrifood chains [1,2]. The modern food supply chain has evolved into a globally interconnected system that spans multiple stages, from agricultural production to primary processing, making the assurance of food quality and authenticity increasingly challenging. Although post-harvest analytical science has been well-established, traditional manual inspection methods often fail in accuracy, speed, and predictive capability. In response, the field has increasingly adopted advanced approaches such as genomics, proteomics, and metabolomics. Furthermore, the integration of smart technologies, artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) has begun to provide new levels of efficiency and transparency across the farm-to-fork continuum [3–6].

Despite these significant technological advances, the implementation of comprehensive farm-to-fork traceability still faces three structural bottlenecks. The first is a predominantly reactive verification paradigm. Most conventional analytical approaches operate ex-post, meaning they are applied after harvest, processing, or market entry primarily to confirm a suspected fraud event. While powerful for post-incident detection, this reactive logic fails to anticipate risk or fully capture the influence of pre-harvest conditions on food composition. The second bottleneck is the persistent reliance on unimodal analytical strategies. Individual spectroscopic techniques or single isotopic markers often provide only partial windows into authenticity; no single modality is universally sufficient to capture the complex pedological, climatic, and management variables that shape a product's origin. The third bottleneck concerns the lack of viability for real-world deployment. Many proposed systems are analytically sophisticated but remain difficult to scale due to high implementation costs, lack of interoperability, and missing frameworks for data governance, particularly for high-value products such as Protected Designation of Origin (PDO) and Protected Geographical Indication (PGI) foods, where regulatory compliance is essential for consumer trust.

To overcome these structural limitations, this review proposes an integrated conceptual framework based on five pillars, moving the field from reactive testing toward a predictive, continuous, and data-driven ecosystem. Rather than treating pre-harvest agronomic data and post-harvest analytical chemistry as separate disciplines, the proposed framework fuses them into a single, multi-dimensional architecture.

The novelty and specific contribution of this review lie in organizing the state-of-the-art literature according to these five pillars. By synthesizing recent advances, this review demonstrates how the integration of smart farming data with advanced analytical chemistry provides a robust solution to the limitations of current traceability models [3–5].

Accordingly, the remainder of this review is structured as follows. Section 2 presents the integrated conceptual framework and explains the predictive feedback logic connecting its five pillars. Pillar I examines pre-harvest monitoring technologies and the capture of the terroir baseline. Pillar II critically evaluates post-harvest analytical fingerprinting, focusing on vibrational spectroscopy and stable isotope ratio mass spectrometry. Pillar III addresses the chemometric and AI-driven data fusion strategies required to overcome unimodal limitations. Pillar IV discusses the digital custody and traceability infrastructures necessary for continuous supply chain tracking. Finally, Pillar V addresses the socio-economic

viability and governance required for industrial adoption, followed by critical applications by food category and a roadmap toward future implementation before main conclusions.

2. Integrated Conceptual Framework for Farm-to-Fork Food Authentication and Traceability

2.1. From Reactive Verification to Predictive Ecosystems

Food authentication has historically operated under a reactive, post-harvest, and unimodal paradigm: a sample arrives at the laboratory, is analysed by a single technique (chromatography, spectroscopy, or isotope-ratio mass spectrometry), and is compared against a reference standard established a posteriori [1,2]. Although analytically robust in controlled settings, this approach suffers from three structural limitations that justify the epistemological reorganisation of the field proposed in this review.

First, there is the isolation of pre-harvest information. The edaphic, microclimatic, and agronomic conditions that shape the isotopic and metabolic chemical fingerprint of a product remain, in most current systems, outside the chain of evidence. The inherent predictive capacity of the terroir concept is thus wasted: the origin signature is not generated in the laboratory, but in the field, throughout the production cycle [6,7]. Traditional post-harvest monitoring is therefore unable to anticipate deviations before the product enters the supply chain.

Second, there is the reliance on unimodal analytical techniques. Previous literature has tended to organise itself around isolated instrumental families (NIR, FTIR, Raman, IRMS, NMR), evaluating their performance independently [8,9]. However, food matrices are inherently complex, and modern adulteration, particularly in high-value products protected by Protected Designation of Origin (PDO) or Protected Geographical Indication (PGI), demands convergent evidence that no single technique can provide on its own [10]. The lack of systematic integration between field sensors, spectroscopic and isotopic fingerprints, and artificial-intelligence tools constitutes a methodological bottleneck that limits discriminating power against sophisticated fraud.

Third, there is limited scalability and insufficiently discussed economic viability for small and medium-sized producers. Centralised laboratory instrumentation, the absence of interoperable standards, and the lack of clear regulatory frameworks have restricted industrial adoption to high-value niches (PDO wines, premium oils, monofloral honey) [11,12]. Most of the literature focuses on analytical precision achieved under optimal laboratory conditions, yet omits critical cost analysis, scalability for medium-sized agri-food operations, and the regulatory frameworks that enable or block adoption in practice [13].

This work proposes a paradigm shift: an integrated five-pillar framework that systematically links pre-harvest data (precision agriculture and the Internet of Things, IoT), post-harvest analytical fingerprints (spectroscopy and isotopes), intelligent data fusion (advanced chemometrics, machine learning, and artificial intelligence), and traceability infrastructure (edge and cloud computing, blockchain), all within a context of viable governance (regulation, cost-effectiveness, and socio-cultural dimensions). This framework not only organises the technologies reviewed in the following sections, but also establishes the conditions of viability for their effective transfer from the laboratory to industrial practice.

2.2. The Five Pillars of the Proposed Framework

The framework is structured into five interdependent layers that operate sequentially and with feedback, transforming field data into verifiable, viable, and scalable authentication evidence (Figure 1).

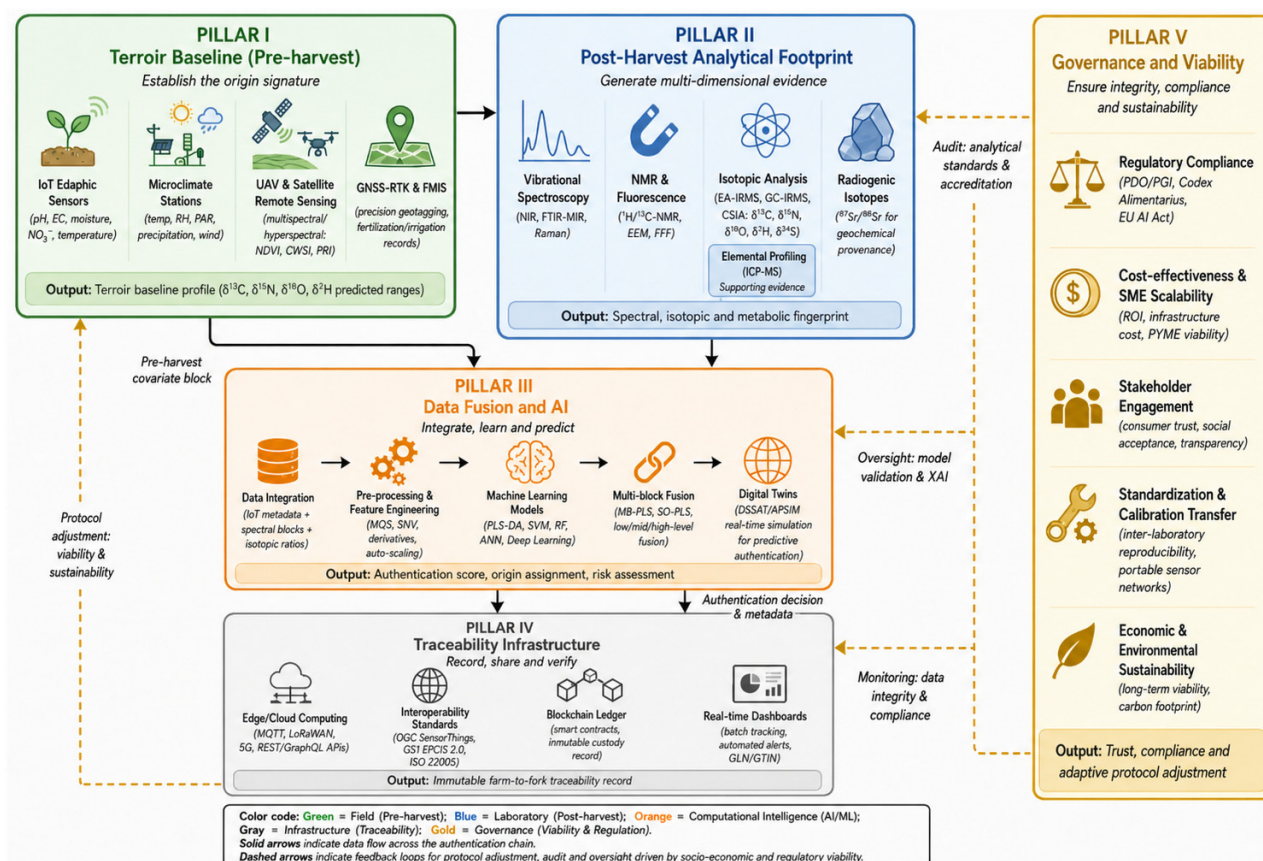


Figure 1. Integrated five-pillar framework linking smart farming data with spectroscopic and isotopic analysis for farm-to-fork food authentication and traceability. Solid arrows indicate data flow; dashed arrows indicate governance feedback and adaptive protocol adjustment.

Pillar I: Terroir Baseline (Pre-harvest)

This pillar comprises the systematic capture of environmental, edaphic, and agronomic variables through in-situ IoT sensors, microclimatic stations, proximal remote sensing (multispectral and hyperspectral UAVs) and satellite platforms, precision GNSS positioning, and farm-management information systems (FMIS) [14,15]. Its function is not merely descriptive, but predictive: it allows the expected ranges of isotopic composition ($\delta^{13}\text{C}$, $\delta^{15}\text{N}$, $\delta^{18}\text{O}$, $\delta^2\text{H}$, $\delta^{34}\text{S}$) and metabolic profile to be estimated before harvest. Applied nitrogen conditions the $\delta^{15}\text{N}$ of plant tissue; soil electrical conductivity acts as a proxy for soil mineralogy, influencing the trace-element profile (Ca, Mg, K, Sr, Fe, Zn); and the hydric and thermal regime defines the isotopic line of local meteoric water, modelling the $\delta^{18}\text{O}$ and $\delta^2\text{H}$ values in the final product [16,17]. This pillar generates the digital origin signature that conditions all subsequent analytical fingerprints.

Pillar II: Post-Harvest Analytical Footprint

This is the set of spectroscopic (NIR, FTIR-MIR, Raman, NMR, fluorescence) and isotopic (EA-IRMS, GC-IRMS, LC-IRMS, CSIA, $^{87}\text{Sr}/^{86}\text{Sr}$) techniques that capture the molecular, structural, and elemental composition of the harvested product [8,18]. This pillar answers the question: what is the product? The choice of technique is not arbitrary; it is defined by the food matrix, the authentication parameter sought (geographical origin, agricultural practice, adulteration), and the requirements of resolution, speed, cost, and sample-preparation needs. As discussed in Section 4, the complementarity between vibrational spectroscopy (functional molecular information) and isotopic analysis (origin and metabolism information) is essential for building convergent evidence.

Pillar III: Data Fusion and Artificial Intelligence

This is the integration layer where data from Pillars I and II are combined through advanced chemometrics (PLS, PCA, LDA, SIMCA) and machine-learning and artificial-intelligence models (SVM, Random Forest, neural networks, deep learning, federated learning) [19,20]. The novelty here lies in the use of pre-harvest data as active explanatory covariates of the predictive model, rather than as passive metadata. Digital twins operate at this level as virtual replicas synchronised with IoT streams that simulate the expected ranges of isotopic and metabolic signatures before laboratory analysis is performed, improving the classification of lots for which the analytical reference database is scarce [21]. Multi-block fusion (MB-PLS, SO-PLS) integrates spectroscopic, isotopic, and environmental blocks into a single classification model, systematically outperforming the discriminating power of single-block models [22].

Pillar IV: Traceability Infrastructure and Data Custody

This is the technological architecture that guarantees the immutability, interoperability, and traceability of the chain of custody. It includes edge and cloud computing, messaging protocols (MQTT, AMQP), geospatial APIs (OGC SensorThings), distributed ledgers (blockchain, DAG), and standardisation (GS1 EPCIS 2.0, ISO 22005:2007, INSPIRE) [23,24]. This pillar transforms analytical data into verifiable regulatory evidence, cryptographically linking the hash of the IRMS or spectroscopic certificate to the pre-harvest IoT record of the same lot, generating continuous digital forensic evidence from field to laboratory.

Pillar V: Governance, Viability, and Socio-Economic Context

This is the transversal layer that evaluates the real feasibility of implementing the framework. It includes: (i) cost–benefit analysis and scalability for small and medium-sized producers; (ii) regulatory and certification frameworks (PDO/PGI, Codex Alimentarius, EU AI Act); (iii) social acceptance, consumer trust, and transparency; (iv) methodological standardisation, transferability of calibrations between portable instruments, and inter-laboratory reproducibility; and (v) environmental sustainability and return on investment of the integrated system [13,25].

2.3. Operational Workflow of the Framework

The framework workflow follows a predictive feedback logic that articulates the five pillars in a continuous cycle:

- (1). Baseline generation. During the production cycle, IoT sensors, UAVs, and satellite remote sensing build the dynamic terroir profile (Pillar I), recording edaphic, microclimatic, and physiological-stress variables with high spatial and temporal resolution.
- (2). Signature prediction. Predictive models (Pillar III) estimate, from the baseline, the expected ranges of isotopes ($\delta^{13}\text{C}$, $\delta^{15}\text{N}$, $\delta^{18}\text{O}$) and metabolites (sugars, amino acids, polyphenols) before harvest. Digital twins generate early warnings of deviation from the expected profile for the zone and variety, allowing corrective interventions or, at minimum, the documentation of anomalies.
- (3). Post-harvest analysis. Spectroscopic and isotopic techniques (Pillar II) confirm or refute the authenticity of the harvested lot, quantifying the actual chemical fingerprint of the product.
- (4). Fusion and decision. Field data and laboratory data are integrated (Pillar III) through multi-level data-fusion strategies (low-, mid-, and high-level), producing an authentication verdict with quantified confidence intervals and identified variables of importance.
- (5). Recording and traceability. The analytical result, together with the lot's chain of custody, is recorded in the distributed infrastructure (Pillar IV), generating an im-

mutable digital passport for the product, consultable by producers, cooperatives, control bodies, and end consumers.

- (6). Viability assessment. Pillar V continuously audits whether the benefits in transparency, fraud reduction, and access to premium markets (PDO/PGI) justify the costs of instrumentation, training, maintenance, and regulatory compliance. This feedback adjusts the framework to specific geographical, economic, and cultural contexts, avoiding the imposition of technologically unviable solutions on small farms.

2.4. Novelty and Specific Contributions of This Review

This review is distinguished from previous work in the food-authentication literature by the following fundamental aspect:

- Proposal of an original five-pillar conceptual framework, in which authentication is not conceived as an isolated laboratory test, but as a predictive ecosystem that begins in the field and culminates in digital certification. Unlike descriptive reviews that catalogue techniques one after another, this work organises knowledge around a functional architecture with a defined data flow and feedback between its components.
- Explicit incorporation of socio-economic and regulatory viability as a structural pillar (Pillar V). Most of the literature focuses on analytical precision achieved under controlled conditions, yet omits critical cost analysis, scalability for small and medium-sized agri-food enterprises, and the regulatory frameworks that enable or block industrial adoption [26]. This review critically discusses these barriers, offering a balanced view between technological potential and implementation reality.
- Reconceptualisation of pre-harvest data as active variables of the predictive model, rather than passive metadata. We argue that integrating the terroir baseline with post-harvest chemometrics through data fusion not only improves classification accuracy, but also enables proactive detection of anomalies before the product enters the supply chain, shifting the authentication paradigm from reactive to predictive.
- Critical comparative analysis of analytical techniques under quantifiable performance criteria (precision, sensitivity, specificity, cost per sample, analysis time, portability, and preparation requirements), allowing the reader to select the optimal strategy according to the application context rather than merely instrumental availability. This approach responds directly to the demand for quantitative comparisons between techniques raised in the specialist literature.
- A well-founded prospective discussion of which technologies possess sufficient maturity for industrial adoption in the next 5–10 years (for example, portable NIR, low-field NMR, blockchain in PDO traceability) versus those that still require rigorous validation under real field conditions (for example, portable laser IRMS, digital twins at commercial scale, federated learning in real agri-food networks). This technology-maturity roadmap allows researchers, industry, and regulators to prioritise investments and standardization efforts.

3. Pillar I: Capture of the Terroir Baseline and Pre-Harvest Technologies

Precision Agriculture (PA), within the framework of the Agriculture 4.0 paradigm, is an agronomic management system that integrates the acquisition and analysis of spatial and temporal data to optimize input use, improve productive efficiency, and support decision-making through continuous monitoring and advanced analytics [26–28]. Within this paradigm, the concept of Smart Farming goes beyond the simple incorporation of field sensors: it articulates a multilevel architecture in which the Internet of Things (IoT), edge and cloud computing, artificial intelligence, and automation converge, forming systems capable of responding in real time to crop conditions [4,29,30]. This technological integra-

tion is particularly relevant for food authentication and traceability, because environmental conditions and management practices during the pre-harvest phase are determining factors in isotopic fractionation processes and in the formation of the metabolomic and spectral profiles that constitute the chemical fingerprint of a food's origin [8,31]. Therefore, combining high-resolution agronomic data with post-harvest analytical techniques makes it possible to build traceability systems grounded in solid physicochemical evidence, which reinforce transparency and origin verification in complex agri-food chains [19,23,31–34].

The pre-harvest phase constitutes the starting point of the farm-to-fork traceability chain. It is in the field where the physicochemical fingerprints that post-harvest analyses must subsequently verify and authenticate are formed [24]. The set of environmental variables (temperature, solar radiation, precipitation), edaphic variables (pH, electrical conductivity, organic matter content), and agronomic variables (cultivated varieties, phytosanitary management, planting density) that characterize a production site throughout a growing season defines what is known as the *terroir* baseline: the physicochemical reference of origin of a given lot, unique and unrepeatable, which conditions both the chemical composition of the product and its potential for geographical authentication [6,7]. The systematic quantification of these variables through IoT sensor networks, capable of recording real-time data on soil, microclimate, and crop status, now constitutes the operational foundation of any robust food authentication system, as it integrates into a digital platform the historical record of agronomic conditions prior to harvest, converting field information into traceable and verifiable evidence [35–37]. Within the integrated framework introduced in Section 2, this baseline constitutes the first active layer of the predictive authentication ecosystem. Table 1 below presents the main pre-harvest sensing technologies and their specific contribution to this baseline.

Edaphic sensors installed in the soil profile enable continuous monitoring of key variables such as volumetric moisture, pH, electrical conductivity (EC), available nitrogen (NO_3^-), and temperature, providing high spatial and temporal resolution information on soil status [38,39]. These parameters have a direct effect on post-harvest isotopic markers. In particular, the source and dose of applied nitrogen condition the $\delta^{15}\text{N}$ value of plant tissue, which constitutes one of the most robust indicators for differentiating organic and conventional production systems [16,40]. Complementarily, soil electrical conductivity acts as a proxy for its physicochemical and mineralogical properties [17], influencing the trace element profile (Ca, Mg, K, Sr, Fe, Zn) that can subsequently be detected in the harvested product using techniques such as ICP-MS, thereby enabling the geochemical traceability of origin [41–43].

IoT-connected microclimatic stations enable continuous monitoring of variables such as temperature, relative humidity, photosynthetically active radiation (PAR), wind, and precipitation, generating a high-resolution hydrothermal record of the plot [15,44]. These factors are primary determinants of isotopic fractionation in plants: temperature regulates evapotranspiration and $\delta^{18}\text{O}$ enrichment in xylem water, while local precipitation defines the isotopic signal relative to the Global Meteoric Water Line [45,46]. Likewise, water availability modulates stomatal conductance and, consequently, the $\delta^{13}\text{C}$ of plant tissue, constituting a robust indicator of water use efficiency (WUE) [47].

On the other hand, UAVs equipped with multispectral and hyperspectral sensors in the VNIR range enable the generation of crop physiological status maps at centimetric resolution [48,49]. Derived indices such as NDVI, NDRE, and CWSI allow quantification of water, nutritional, and biotic stress [50,51]. This stress induces changes in the secondary metabolite profile, including phenolic compounds, carotenoids, and terpenes, which can be detected by post-harvest NIR and Raman spectroscopy, establishing a reproducible link between pre-harvest conditions and the chemical fingerprint of the final product [52,53].

Table 1. Pre-harvest monitoring technologies and their contribution to the terroir baseline for food authentication.

Sensor/Technology	Sensor Type	Measured Parameters	Platform	Spatial Res.	Contribution to the Terroir Baseline
IoT edaphic sensors	Electrochemical (pH, NO ₃ [−] , Eh), capacitive/FDR (moisture), TDR	Vol. moisture, pH, EC, NO ₃ [−] , soil temperature, redox potential (Eh)	In-situ IoT node	Point-scale (cm)	Determines $\delta^{15}\text{N}$ according to N source (organic vs. synthetic); EC acts as a proxy for soil mineralogy, conditioning the elemental profile (Ca, Mg, K, Fe, Zn) and, indirectly, geochemical provenance markers such as $^{87}\text{Sr}/^{86}\text{Sr}$
IoT microclimatic stations	Thermohygrometer, pyranometer, tipping-bucket rain gauge, anemometer	Temperature, RH, PAR, wind speed and direction, precipitation	Fixed IoT mast/agrometeorological station	Local (m–km)	Conditions $\delta^{18}\text{O}$ and $\delta^2\text{H}$ (local temperature and precipitation relative to the Global Meteoric Water Line) and $\delta^{13}\text{C}$ (WUE under water stress through stomatal conductance)
Multispectral/hyperspectral UAV	Multispectral frame sensor (5–10 bands, narrow-pass filters); VNIR push-broom hyperspectral camera (400–1000 nm); thermal IR sensor (LWIR)	NDVI, NDRE, GNDVI, EVI (vigor); CWSI, WBI (water stress); PRI, PSRI, Chl (biotic stress and senescence); canopy temperature	Multirotor/fixed-wing UAV	2–15 cm GSD (depending on flight altitude and sensor)	Pre-harvest stress map at plant scale; conditions the secondary metabolite profile (phenols, carotenoids, terpenes) detectable by post-harvest NIR and Raman; correlates with $\delta^{13}\text{C}$ via photosynthetic efficiency
Multispectral and thermal satellite imagery	Sentinel-2 MSI (13 bands, 443–2190 nm); Landsat-9 OLI-2 + TIRS; PlanetScope SuperDove	NDVI, EVI, NDWI, phenology, LAI (all sensors)	Earth observation satellite (orbital platform)	3 m (PlanetScope); 10–60 m (Sentinel-2); 30 m (Landsat-9 OLI); 100 m (Landsat-9 TIRS)	Multitemporal characterization of terroir at regional scale; delineation and monitoring of PDO/PGI zones; detection of interannual phenological anomalies affecting product chemical composition
Precision GNSS (RTK)	Multi-constellation GPS/GLONASS/Galileo/BeiDou receivers with RTK or PPP correction	Latitude, longitude, ellipsoidal altitude, plot boundaries, sampling point coordinates	Agricultural machinery/handheld/UAV base station	<2 cm (RTK)/<10 cm (PPP)	Centimetric geotagging of plots for spatial traceability of multi-source IoT data; altitude for correction of $\delta^{18}\text{O}$ and $\delta^2\text{H}$ isotopic models according to altitudinal gradient (~2.5‰/100 m)
Farm Management Information System (FMIS) and digital agronomic records	Cloud-based FMIS software; mobile field notebook applications; integration with IoT sensor APIs	Fertilization type, dose and date; phytosanitary applications; irrigation (volume, frequency); cultivated variety; sowing and harvest dates	Cloud platform/tablet/smartphone	— (documentary record, non-spatial)	Audited management history: type of N applied for $\delta^{15}\text{N}$; irrigation practices for $\delta^{13}\text{C}$ and $\delta^{18}\text{O}$; S source for $\delta^{34}\text{S}$; documentary basis for organic certification and PDO

Note: EC: electrical conductivity; Chl: chlorophyll content (spectral index); CWSI: Crop Water Stress Index; PDO/PGI: Protected Designation of Origin/Protected Geographical Indication; Eh: soil redox potential; EVI: Enhanced Vegetation Index; FDR: frequency domain reflectometry; FMIS: Farm Management Information System; GNDVI: Green Normalized Difference Vegetation Index; GSD: Ground Sampling Distance; RH: relative humidity; ICP-MS: inductively coupled plasma mass spectrometry; LAI: leaf area index; LST: Land Surface Temperature; LWIR: long-wave infrared; NDRE: Normalized Difference Red Edge Index; NDVI: Normalized Difference Vegetation Index; NDWI: Normalized Difference Water Index; PAR: photosynthetically active radiation; PPP: precise point positioning; PRI: Photochemical Reflectance Index; PSRI: Plant Senescence Reflectance Index; RTK: real-time kinematic; TDR: time domain reflectometry; TIRS: Thermal Infrared Sensor; VNIR: visible and near-infrared; WBI: Water Band Index; WUE: water use efficiency.

Earth observation satellite platforms such as Sentinel-2 MSI, Landsat-9, and PlanetScope enable the multitemporal characterization of terroir at landscape scale through derived products such as NDVI, Enhanced Vegetation Index, NDWI, and land surface temperature, facilitating the dynamic delineation of zones associated with designations of origin and the detection of interannual phenological anomalies that affect the chemical composition of the product [54]. Evidence has also emerged of correlations between spectral indices and soil microbial diversity, opening new avenues for geographic authentication based on biophysical proxies [21].

In parallel, high-precision geotagging via RTK GNSS ensures centimetric spatial traceability of plots, allowing environmental and edaphic data to be anchored to verifiable coordinates, while the recorded altitude enables corrections to be applied in $\delta^{18}\text{O}$ and $\delta^2\text{H}$ isotopic models in accordance with documented altitudinal gradients [55,56]. These spatial delimitations also constitute the integration unit for multi-source data layers spanning in-situ sensors, UAVs, and satellites.

Finally, farm management systems (FMIS) and digital agronomic records consolidate the agronomic management history: fertilization, irrigation, and phytosanitary applications; in traceable platforms, providing the causal context needed to interpret isotopic biomarkers ($\delta^{15}\text{N}$, $\delta^{13}\text{C}$, $\delta^{18}\text{O}$), while their integration with blockchain technologies ensures the immutability and auditability of records, thereby strengthening origin certification systems [57].

4. Pillar II: Post-Harvest Analytical Fingerprint

The post-harvest stage has traditionally constituted the core of food authentication workflows [1,2,8]. However, when operating as an isolated verification layer, analytical chemistry behaves reactively rather than predictively [1,2,58,59]. To resolve this paradigm, Pillar II redefines post-harvest analytical techniques—spectroscopies and isotopic analyses—not as standalone diagnostic tools, but as dynamic chemical fingerprints designed to be mathematically coupled with the pre-harvest terroir baseline (Pillar I) [6–8,18].

4.1. Vibrational and Complementary Spectroscopy

Spectroscopic platforms allow rapid, non-destructive molecular interrogation with minimal or no sample preparation [60,61]. Their key strength lies in capturing holistic molecular signatures directly from complex matrices without requiring tedious chemical separations [8,62,63].

4.1.1. Near-Infrared (NIR) Spectroscopy

Spanning 780 to 2500 nm, NIR spectroscopy measures overtones and combination bands of O–H, N–H, and C–H stretching vibrations, providing intrinsic sensitivity for quantifying moisture, lipids, and proteins across diverse matrices [64–68]. Recent advances have expanded its utility from basic composition to predicting complex sensory and functional traits: Sun et al. [69] demonstrated that combining NIR with PLS regression allows the prediction of both chemical and sensory quality attributes in tomatoes. Fulladosa et al. [70] validated online NIR sensors to characterize salt content in canned tuna, achieving accuracy levels compatible with nutritional labeling requirements. NIR is increasingly replacing traditional chromatographic methods like GC because it provides a rapid, non-destructive, and reagent-free alternative that can be utilized in situ or at-line, eliminating the extensive sample preparation and destruction required by GC.

Despite its high analytical throughput and ease of use, NIR suffers from broad, highly overlapping absorption bands, low chemical specificity for trace adulterants, and physical light-scattering interferences [65,67,68]. As highlighted by Squeo et al. [63], a major institu-

tional bottleneck remains the considerable gap between the scientific maturity of NIR and its formal adoption into official methods of analysis. Furthermore, variable selection strategies (e.g., interval-based approaches) are critical to prioritize regions of genuine chemical relevance rather than processing non-informative spectral noise [71,72].

4.1.2. Mid-Infrared (MIR) and FTIR Spectroscopy

Operating in the 400–4000 cm^{-1} region, MIR accesses fundamental molecular vibrations, yielding superior chemical specificity compared with NIR [9,60]. The introduction of Fourier-transform infrared (FTIR) instruments enabled rapid, multiplex acquisition with high signal-to-noise performance [71,73]. Attenuated Total Reflectance (ATR-FTIR) has streamlined liquid and solid analysis, proving especially effective for detecting adulteration in olive oil (blending with cheaper vegetable oils) [73,74] and dairy products [71,73].

The integration of focal plane array (FPA) detectors has enabled FTIR imaging (MIR hyperspectral imaging), offering micro-spatial mapping to identify heterogeneous solid adulterants such as microplastics or melamine particles [75]. However, water strongly absorbs MIR radiation, severely limiting direct transmission measurements in high-moisture matrices unless specialized ATR geometries or sample dehydration protocols are implemented [9,60,74].

4.1.3. Raman Spectroscopy

Raman spectroscopy relies on inelastic light scattering to probe changes in molecular polarizability [61,62]. Because it is largely insensitive to water, it offers significant advantages for aqueous and high-moisture matrices [60–62]. Advanced modalities include:

Surface-Enhanced Raman Spectroscopy (SERS): Pushes sensitivity to trace levels for rapid detection of pesticides, mycotoxins, and contaminants [76,77].

Spatially Offset Raman Spectroscopy (SORS): Allows non-destructive inspection through opaque packaging [76,77].

Raman Hyperspectral Imaging (RHI): Maps micro-spatial chemical distributions in complex horticultural products [78].

Nutritional & Contaminant Analysis: Moe Htet et al. [79] applied PLS-assisted Raman for non-destructive quantification of α -tocopherol in vegetable oils, while Khongkaew et al. [80] developed quantitative models to detect lead contamination in turmeric powder despite intense fluorescence.

Historically, Raman adoption was hindered by intrinsically weak signals and severe fluorescence background interference from complex chromophores [62,81]. While modern baseline-correction algorithms and SERS substrates mitigate this, SERS introduces operational challenges regarding substrate cost and batch-to-batch reproducibility [62,81].

4.1.4. UV-Vis and Fluorescence Spectroscopy

UV-Vis spectroscopy (200–800 nm) targets electronic transitions in chromophores, pigments, and phenolic compounds [8,60,82]. Modern low-cost optical components have enabled smartphone-based diagnostic platforms for point-of-need screening [83].

Front-Face Fluorescence (FFF) bypasses light scattering in opaque or turbid matrices (cheeses, butter, meat) [73,74]. When combined with Excitation–Emission Matrices (EEM) and deconvoluted via Parallel Factor Analysis (PARAFAC) [73,84], fluorescence selectively probes intrinsic fluorophores (aromatic amino acids, riboflavin, oxidation products) [72]. Nevertheless, UV-Vis lacks structural specificity and is easily affected by matrix turbidity [8,82]. Fluorescence, while exceptionally sensitive, is restricted to molecules containing fluorescent chromophores and requires multi-way chemometrics to handle overlapping EEM landscapes [73,84].

4.1.5. Nuclear Magnetic Resonance (NMR) Spectroscopy

High-resolution ^1H and ^{13}C NMR spectroscopy provides inherently quantitative, non-targeted metabolomic profiles (amino acids, sugars, organic acids) from complex mixtures with unparalleled inter-laboratory reproducibility [85–87]. Global ^1H NMR profiling is routinely screened against standardized databases for wine, honey, juice, and olive oil authenticity [75,85,86].

High-field NMR requires substantial capital investment, liquid cryogenics, and specialized expertise, restricting its deployment to centralized laboratories [85,86]. However, ^1H NMR has achieved real-world industrial implementation for routine wine and honey screening in commercial facilities [10,38,85]. To bridge the gap toward broader industrial adoption, cryogen-free benchtop NMR (43–100 MHz) trades spectral resolution for portability, offering a practical path toward factory-floor screening and adulterant detection [88,89].

4.2. Isotopic Analysis

Stable and radiogenic isotope techniques represent the benchmark for origin verification, production practice validation, and process authentication [58,59,90,91]. IRMS has become critically important in recent years because isotopes provide a direct, unfalsifiable link to soil geochemistry and local climatic water lines, which complex supply chains demand for Protected Designation of Origin (PDO) verification as shown in Figure 2.

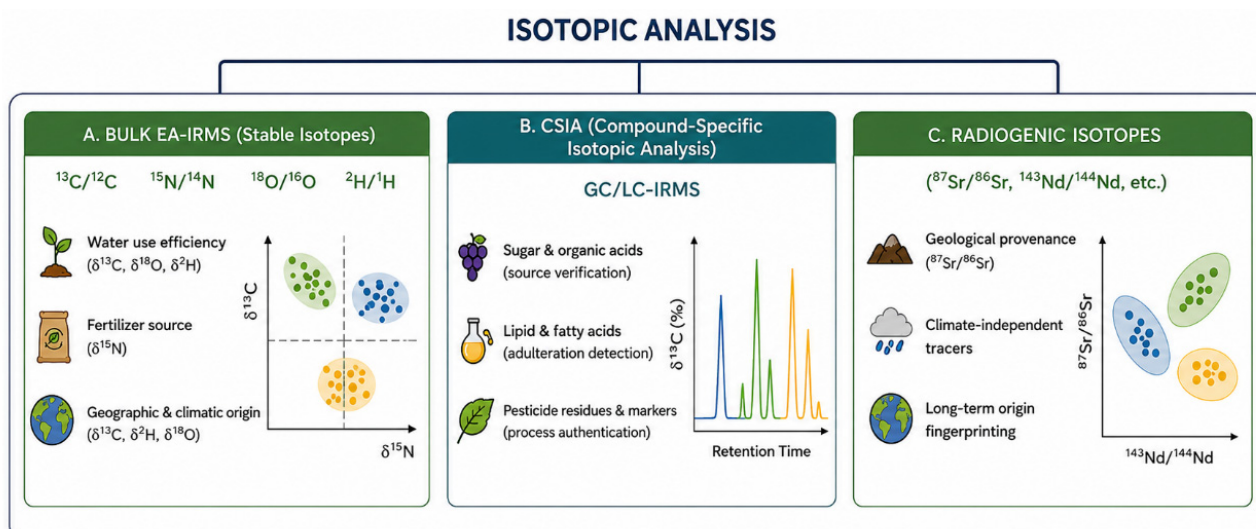


Figure 2. Overview of the main isotopic analytical approaches used in agricultural authentication. Bulk EA-IRMS, CSIA, and radiogenic isotope analysis provide complementary fingerprints for assessing geographical origin, production practices, and food authenticity.

4.2.1. Stable Isotopes $\delta^{13}\text{C}$, $\delta^{15}\text{N}$, $\delta^{18}\text{O}$, $\delta^2\text{H}$, $\delta^{34}\text{S}$ and EA-IRMS

Elemental Analysis coupled to Isotope Ratio Mass Spectrometry (EA-IRMS) measures natural isotopic variations driven by physiological and environmental fractionation [90,92,93]:

$\delta^{13}\text{C}$: Differentiates C3 vs. C4 photosynthetic pathways and reflects plant water-use efficiency (WUE) under hydric stress [18,45,47].

$\delta^{15}\text{N}$: Serves as a direct biomarker for nitrogen fertilization regimes, distinguishing synthetic fertilizers from organic manure [16,40,94].

$\delta^{18}\text{O}$ and $\delta^2\text{H}$: Track meteoric water sources, evapotranspiration, local ambient temperature, and altitudinal gradients [45,46,95].

$\delta^{34}\text{S}$: Reflects underlying soil geochemistry and atmospheric sulfur deposition [96,97].

4.2.2. Compound-Specific Isotope Analysis (CSIA)

By coupling Gas or Liquid Chromatography to IRMS (GC-IRMS, LC-IRMS) [92,93], CSIA measures isotopic ratios of individual target molecules (e.g., specific fatty acids, sugars, amino acids, volatile aroma terpenes) rather than bulk matrices [98,99]. This provides target-specific resolution capable of exposing sophisticated fraud, such as distinguishing authentic honey from C4 sugar-syrup adulteration, identifying synthetic flavorings, or verifying extra virgin olive oil provenance [98–100].

4.2.3. Multi-Isotope Fingerprinting and $^{87}\text{Sr}/^{86}\text{Sr}$

Integrating multiple stable isotopes into a unified fingerprint significantly enhances classification accuracy across complex food matrices, including meat [101], seafood [102], fruits [97,103], olive oil [104,105], wine [95,106], coffee [107], nuts [108], and honey [109].

To overcome the limitation of stable isotopes being influenced by seasonal climatic shifts, radiogenic strontium isotope ratios $^{87}\text{Sr}/^{86}\text{Sr}$ are incorporated [90,110]. Strontium ratios pass un-fractionated from bedrock soil into plant tissues and animal products, providing a pure geological footprint of provenance independent of climate fluctuations [110–112].

4.3. Miniaturization and Portable Instrumentation

The transition from centralized testing to point-of-need inspection across the supply chain is driven by MEMS, linear variable filters (LVF), compact array detectors, and edge-computing architectures [11,12,63,113]. Miniaturized NIR and Raman devices allow rapid quality control at processing plants, retail nodes, and field borders [61,114,115].

However, real-world deployment faces critical implementation barriers. Portable instruments inherently exhibit lower signal-to-noise ratios, restricted spectral ranges, and higher sensitivity to environmental perturbations such as ambient light and field temperature fluctuations [11,63,113]. Furthermore, transferring multivariate calibration models across multiple secondary hand-held units without loss of predictive power remains a severe operational hurdle [116]. Advanced algorithms, such as transfer learning, deep learning architectures, and ensemble pre-processing, are actively being developed to resolve these bottlenecks [11,12,49,117].

4.4. Comparative Assessment of Analytical Techniques

To guide practical deployment, Table 2 provides a quantitative and operational comparison of post-harvest analytical platforms [8,18,60].

Table 2. Quantitative comparative assessment of post-harvest analytical techniques for food authentication.

Analytical Technique	Physicochemical Principle	Primary Detected Markers	Typical Precision/Accuracy	Analysis Time Per Sample	Relative Cost Per Sample	Sample Prep Required	Portability & Field Readiness	Representative Food Matrix
NIR Spectroscopy	O–H, N–H, C–H overtones & combinations [67,68]	Moisture, lipids, proteins, sugars	Moderate-High (RMSEP ~1–3%) [69,70]	<1 min [64]	Very Low (<\$2)	None to Minimal [65,66]	High (Handheld MEMS/LVF) [11,12]	Grains, dairy, meat, fruit [64,65]
FTIR/ATR-MIR	Fundamental molecular vibrations [9,60]	Organic functional groups, fatty acids, triacylglycerols [73,74]	High (>95% class accuracy) [71,73]	1–3 min [73]	Low (\$2–\$5)	Low (Direct ATR placement) [74]	Moderate (Bench-top/Compact) [60]	Edible oils, fruit juices, honey [71,73,74]
Raman Spectroscopy	Inelastic photon scattering (polarizability) [61,62]	Carotenoids, terpenes, unsaturated lipids, pigments [77,79]	High (>90% accuracy) [79,80]	1–5 min [79]	Low-Moderate (\$5–\$15)	None (SORS through packaging) [77,81]	High (Point-and-shoot handhelds) [61,80]	Extra virgin olive oil, spices, wine [92–94]

Table 2. Cont.

Analytical Technique	Physicochemical Principle	Primary Detected Markers	Typical Precision/Accuracy	Analysis Time Per Sample	Relative Cost Per Sample	Sample Prep Required	Portability & Field Readiness	Representative Food Matrix
EEM/FFF Spectroscopy	Fluorophore excitation & emission [73,82]	Aromatic amino acids, riboflavin, phenolic profiles [73,84]	High (Selective trace detection) [72,84]	3–10 min [84]	Low (\$3–\$8)	Low-Moderate (Front-face adapters) [73]	Low-Moderate [83]	Wine, honey, cheese, butter [73,74]
¹ H/ ¹³ C High-Field NMR	Nuclear spin resonance in magnetic fields [85,86]	Global untargeted metabolome (amino acids, sugars, acids) [75,85]	Very High (>98% reproducibility) [86,87]	10–20 min [85]	High (\$50–\$150)	Moderate (Extraction/Solvent addition) [85]	Very Low (Centralized lab only) [85,86]	Wine, honey, juice, premium oils [75,85]
Benchtop Low-Field NMR	Low-field nuclear spin resonance (43–100 MHz) [88,89]	Bulk lipids, moisture, major sugar profiles [88]	Moderate-High (>90% screening accuracy) [88,89]	5–10 min [88]	Moderate (\$15–\$30)	Low-Moderate [89]	Moderate (At-line/Factory floor) [88,89]	Edible fats, honey supplements [88,89]
Bulk EA-IRMS	Stable isotope ratios (δ ¹³ C, δ ¹⁵ N, δ ¹⁸ O, δ ² H, δ ³⁴ S) [90,91]	Isotopic fractionation signatures [58,93]	High (Precision ≤0.1–0.3‰) [92]	15–30 min [92]	Moderate-High (\$30–\$80)	Moderate (Drying, encapsulation) [18,42]	Low (High-precision benchtop) [58]	Wine, olive oil, honey, meats [101,104]
CSIA (GC/LC-IRMS)	Isotopic analysis of individual compounds [92,98]	Compound-specific δ ¹³ C, δ ² H of fatty acids/sugars [98,99]	Very High (Targeted precision) [98]	45–90 min [98]	Very High (\$100–\$250)	High (Chromatographic extraction) [92,99]	Laboratory only [92]	Premium olive oil, vanilla, honey [98,99]
TIMS/MC-ICP-MS	Radiogenic strontium ratios (87Sr/86Sr) [90,110]	Soil geological provenance markers [110,111]	Ultra-High (Precision ≤0.00005) [110]	2–4 h [110]	Very High (>\$200)	Very High (Acid digestion, ion exchange) [110,112]	Laboratory only [110]	Wine, cheese, avocado, coffee [103,112]

5. Pillar III: Data Fusion, Chemometrics, and Artificial Intelligence

In modern authentication architectures, raw analytical signals carry minimal utility in isolation [8,62,72,118]. The core capability resides in mathematical pipelines that extract latent chemical information, remove physical artifacts, and fuse heterogeneous data streams [119–121].

5.1. Data Pre-Processing and Exploratory Analysis

Mathematical pre-processing isolates true chemical variance from physical, optical, and instrumental artifacts [122,123].

Spectroscopic Pre-Processing

- Physical scattering, sample particle size variations, and baseline drifts are corrected using multiplicative, derivative, and orthogonal projection algorithms [124]:
- SNV & MSC/EMSC: Standard Normal Variate (SNV) normalizes spectral intensity by centering and scaling each spectrum [124]. Multiplicative Scatter Correction (MSC) and Extended MSC (EMSC) regress spectra against an ideal mean reference to model physical light-scattering effects [124,125].
- Normalization Methods: Probabilistic Quotient Normalization (PQN) accounts for dilution in biological extracts [126], while Area, Unit Vector, and Min-Max Normalization compensate for laser power fluctuations or concentration differences.
- Smoothing & Derivatives: Savitzky–Golay Smoothing and Derivatives compute moving polynomial fits [127,128]. First derivatives remove baseline offsets, while second derivatives eliminate linear slopes and resolve overlapping peak structures [127,128].
- Orthogonal Signal Correction (OSC) & EPO: OSC removes spectral variance orthogonal to the response variable (e.g., detector drift) [118]. External Parameter Orthogonal-

ization (EPO) eliminates variance induced by external environmental factors, such as temperature or sample moisture [129].

- Automated & Ensemble Pre-Processing: Recent workflows use Design of Experiments (DoE) [123] or ensemble methods [117] to systematically evaluate and fuse multiple pre-processing sequences, avoiding subjective user bias.

Isotopic Standardization

Isotope Ratio Mass Spectrometry (IRMS) generates discrete, low-dimensional datasets [18,42]. Pre-processing requires rigorous delta (δ) normalization against international reference standards (e.g., VSMOW, VPDB) to ensure global inter-laboratory comparability [18,42]. Variables are subsequently subjected to auto-scaling (z-score standardization), ensuring that trace isotopes carry equal statistical weight alongside dominant elemental concentrations [8,130].

Exploratory Visualization

Unsupervised Principal Component Analysis (PCA) is universally deployed to inspect raw data structures, detect physical outliers, and visualize natural clustering patterns (e.g., origin or variety) prior to supervised modeling [131].

5.2. Multivariate Classification and Calibration Models

When transitioning from exploration to classification, algorithm selection must balance predictive accuracy, non-linear handling, and model interpretability [119,121].

Partial Least Squares (PLS/PLS-DA): PLS regression [118] and PLS Discriminant Analysis [132] remain the standard linear benchmarks for collinear spectroscopic data [65,69,70]. However, PLS assumes linear relationships between spectral intensities and target classes [118].

Non-Linear AI Classifiers (SVM, Random Forest, Deep Learning): Food matrices are subject to complex non-linear biological, climatic, and processing variations. Support Vector Machines (SVM) construct non-linear hyperplanes using kernel functions, significantly outperforming PLS-DA when class boundaries overlap [8,76]. Random Forests (RF) evaluate complex interaction terms across heterogeneous data types without over-fitting [8,76]. Deep Neural Networks (CNNs) extract hierarchical feature representations directly from raw multi-channel signals, bypassing manual feature selection [19,20].

Calibration Transfer: Industrial deployment across supply chain nodes relies on model transfer strategies (e.g., wavelength selection, model updating) originally developed for industrial process control [116,133] to maintain predictive accuracy across different secondary handheld devices [117,134].

Model Interpretability and “Black-Box” Risks: While deep learning models achieve high classification accuracy, their “black-box” nature creates regulatory friction and public mistrust [135]. In legal origin disputes, regulators require transparent justifications [136,137]. Explainable AI (XAI) frameworks (e.g., SHAP, LIME) are increasingly applied to map neural network decisions back to specific, chemically meaningful spectral bands or isotopic features, restoring scientific interpretability and regulatory compliance [136,137].

5.3. Chemometrics in Isotopic Analysis

Because isotopic variations between authentic and fraudulent products are often subtle relative to natural biological background variance [8,94], univariate thresholding is insufficient. ANOVA and PCA identify diagnostic isotopic subsets ($\delta^{13}\text{C}$, $\delta^{15}\text{N}$, $\delta^{18}\text{O}$, $\delta^2\text{H}$, $\delta^{34}\text{S}$, $^{87}\text{Sr}/^{86}\text{Sr}$) [94]. Supervised linear discriminants (LDA, OPLS-DA) and non-linear classifiers (SVM, RF) combine multi-isotope ratios with elemental profiles (ICP-MS) [8,76].

Rigorous validation protocols—including external validation with independent commercial batches, permutation testing, and reporting sensitivity/specificity—are now mandatory to prevent over-optimistic classification [94].

5.4. Multi-Block Data Fusion Strategies

Data fusion integrates multi-instrument outputs into a unified decision matrix, overcoming the inherent limitations of single-technique verification. While traditional PLS is highly interpretable, AI-based non-linear classifiers (SVM, RF, Deep Learning) are beginning to outperform PLS methods because food matrices are subject to complex non-linear biological and climatic variations. Consequently, multi-block data fusion is considered the future direction of food authentication, as it drastically reduces false-positive rates by forcing fraudsters to mimic multiple orthogonal signatures simultaneously [22,76].

Fusion Levels

- (1). Low-Level Fusion: Concatenates raw measurement matrices (e.g., NIR + MIR spectra) before modeling [8,76]. It preserves all raw information but suffers from massive dimensionality, differing scaling units, and noise propagation [8,76].
- (2). Mid-Level (Intermediate) Fusion: Extracts key latent variables (e.g., PCA scores, selected spectral wavelengths, discrete isotope values) from each platform and merges these descriptors into a joint block [8,76]. As demonstrated by Stocco et al. [138] in PDO cheeses, combining NIR and Raman feature blocks significantly improves classification performance over single-sensor models.
- (3). High-Level (Decision-Level) Fusion: Combines independent prediction probabilities from separate classification models (e.g., combining an NIR PLS-DA verdict with an IRMS Random Forest verdict) via voting or Bayesian rules to produce a final consensus decision [8].

5.5. Agricultural Digital Twins and Pre-Harvest Predictive Modeling

Digital Twins represent virtual replicas of agricultural plots synchronized in real time with field IoT streams (Pillar I) and crop growth simulation models (e.g., DSSAT, APSIM) [14,139–141].

Rather than waiting for post-harvest testing, Digital Twins simulate the expected baseline ranges of isotopic composition ($\delta^{13}\text{C}$, $\delta^{18}\text{O}$) and metabolic profiles prior to harvest based on microclimatic and hydric stress records [139,141]. When post-harvest laboratory testing is performed (Pillar II), the pre-harvest model acts as an active probabilistic covariate in Sequential and Orthogonalized PLS (SO-PLS) [22] or Multi-Block PLS (MB-PLS) algorithms [20,142]. This drastically improves classification accuracy for protected designations (PDO/PGI) where authentic reference database samples are naturally scarce [20,139].

5.6. MLOps, Federated Learning, and Transfer Learning

Deploying AI models across real-world agri-food networks introduces operational challenges that require modern MLOps pipelines [20,37]:

Federated Learning: Enables decentralized model training across multiple competitive agricultural cooperatives [24,136]. Individual farms train local AI models on their proprietary IoT and agronomic data, sharing only updated model weights with a central server. This preserves commercial data privacy while building robust, network-wide authentication models [24,136].

Transfer Learning & Calibration Transfer: Addresses instrument-to-instrument variation and seasonal shifts [11,12,116]. By fine-tuning pre-trained deep learning architectures using a small subset of new seasonal or secondary-device samples, transfer learning

maintains high prediction accuracy without requiring complete, expensive model recalibration [11,12,116].

6. Critical Applications by Food Category

The practical implementation of farm-to-fork authentication frameworks relies on translating complex analytical signals into clear answers regarding food origin, quality, and safety. Across diverse food commodities, the combination of isotopic ratios, spectroscopic fingerprints, and smart agricultural data has proven highly effective in exposing fraud and validating label claims [105,143]. The following subsections explore how these integrated approaches are currently applied to major food and beverage categories.

The real value of integrated analytical approaches becomes clearer when they are tested across different food categories, because each matrix brings its own challenges in composition, variability, and fraud vulnerability. Some products are best distinguished through isotopic signatures linked to origin and farming practice, while others respond more strongly to spectroscopic fingerprints or to combined multi-source models. Table 3 captures this diversity well by showing how isotopic and spectroscopic techniques, together with pre-harvest information, can be adapted to different foods and beverages. In doing so, it highlights not only the technical flexibility of these methods, but also their practical relevance for routine traceability.

Table 3. Applications of isotopic and spectroscopic analytical techniques integrated with pre-harvest data for food authentication.

Food Category	Primary Analytical Challenge	Spectroscopic Techniques	Isotopic/Elemental Techniques	Integration with Smart Farming/IoT
Plant pathologies and crop protection	Early disease detection; differentiation between management systems.	NIR and Raman for detecting stress-related metabolic changes and disease-linked spectral fingerprints.	EA-IRMS for nitrogen-related differentiation linked to fertilizer source and crop management.	Correlation with UAV stress indices and field monitoring data in precision agriculture workflows.
Beverages (wine, spirits, coffee)	Geographical origin, vintage consistency, and adulteration control are highlighted as core authentication targets.	NIR, Raman, and NMR support rapid fingerprinting and metabolomic profiling of beverage matrices.	IRMS and related isotopic approaches are presented as robust tools for origin and production-condition verification.	Digital traceability systems can link pre-harvest field data with post-harvest authentication records across the supply chain.
Cereals, fruits, and vegetables	Verification of origin, production system, and quality-linked compositional variation.	NIR and MIR are described as suitable for rapid, non-destructive classification of composition and provenance.	IRMS is used for tracing geographic origin, water regime, and fertilization history through stable isotope ratios.	Links can be established between isotopic signatures and pre-harvest moisture, temperature, and crop-stress data.
Animal-derived foods (dairy and meat)	Authentication of feeding regime, production origin, and compositional differences across systems.	NIR and NMR support rapid compositional screening and broader metabolomic discrimination.	Stable isotope approaches are relevant for linking feed source, water origin, and management history to the final product.	Farm records and environmental monitoring provide contextual variables that strengthen traceability interpretation.

6.1. Plant Pathologies and Precision Agriculture

Managing plant diseases has historically been a reactive and broad-spectrum effort, but precision agriculture is changing how crops are monitored, protected, and treated [144]. Instead of applying the same treatment across an entire field, farmers can now respond to

disease pressure in a more localized and efficient way, recognizing that crops, soils, and pathogens do not behave uniformly in space or time [145]. This shift is important not only for protecting yields, but also for reducing unnecessary pesticide use and supporting more sustainable production systems [145].

Today, the management of plant pathologies is increasingly supported by digital tools such as smart sensors, multispectral imaging, and artificial intelligence models capable of identifying symptoms with high precision [145,146]. Among these tools, deep learning approaches, especially convolutional neural networks, have shown strong performance for real-time diagnosis of plant diseases under practical agricultural conditions [146]. Their value lies in allowing earlier detection, faster decision-making, and more targeted interventions before a disease spread across the whole field [146].

At a broader level, current research shows that precision agriculture is becoming one of the main frameworks for modern plant health management, combining diagnosis, prediction, and site-specific action in a single system [144,145]. In this sense, plant pathology is no longer limited to identifying a disease after damage appears; it is increasingly oriented toward anticipation, continuous monitoring, and precise response [144]. This integration between agronomy, data science, and crop protection is shaping a more resilient and efficient model of agriculture for the coming years [145,146].

6.2. Edible Oils and Fats

Edible oils, particularly extra virgin olive oil, are among the most frequently adulterated food products globally due to their high commercial value and complex supply chains. Spectroscopic and isotopic techniques have become the primary line of defense against both economic adulteration and false geographical declarations [31,105].

Stable isotope ratio analysis (SIRA) is particularly powerful for tracing the geographical origin of olive oils because the isotopic signatures of carbon ($\delta^{13}\text{C}$), hydrogen ($\delta^2\text{H}$), and oxygen ($\delta^{18}\text{O}$) are directly influenced by the specific climatic and pedological conditions of the olive grove [100]. For example, Tarapoulouzi, Skiada, et al. [105] demonstrated the successful chemometric discrimination of the geographical origin of three Greek cultivars of olive oils by relying on stable isotope ratios, emphasizing that $\delta^{18}\text{O}$ and $\delta^2\text{H}$ are the most critical markers for capturing regional climatic nuances. To achieve even finer granularity, recent approaches utilize Compound-Specific Isotope Analysis (CSIA) to measure the carbon isotope ratios of individual fatty acids, providing an isotopic fingerprint that is exceptionally difficult for fraudsters to mimic [100].

Parallel to isotopic methods, vibrational spectroscopy is widely employed to detect the illicit blending of premium olive oils with cheaper botanical alternatives, such as hazelnut, corn, or refined pomace oils. Fourier-transform mid-infrared (FT-MIR) and NIR spectroscopy, when coupled with multivariate models like PLS-DA or SVM, can detect adulterants at low single-digit percentages by identifying deviations in the triacylglycerol backbone and minor lipid components [74]. Furthermore, these techniques are increasingly used to assess quality degradation parameters, such as free acidity and peroxide value, enabling rapid, reagent-free grading of oils at the point of reception [74].

6.3. Beverages: Wine, Spirits, Coffee, and Tea

The beverage sector relies heavily on terroir, traditional processing, and strict geographical indications to define product value. Consequently, verifying the origin and composition of wines, spirits, coffee, and tea has driven significant analytical innovation [143].

In wine authentication, the primary analytical challenges are verifying geographical origin, confirming the declared vintage, and detecting illicit practices such as chaptalization (the illegal addition of sugar to boost alcohol content) or watering down [143]. Site-specific

Natural Isotope Fractionation-Nuclear Magnetic Resonance (SNIF-NMR) and IRMS are the official methods recognized by the International Organisation of Vine and Wine (OIV) for detecting added sugars, as the isotopic ratio of deuterium to hydrogen in the ethanol molecule clearly distinguishes beet or cane sugar from naturally fermented grape sugars. Beyond standard regulatory methods, Koidis et al. [143] highlighted how the integration of elemental profiling (via ICP-MS) with chemometrics allows for the highly accurate geographical discrimination of wines and beers by tracing the soil's mineral signature directly into the finished beverage.

In addition to elemental and isotopic markers, UV-Vis, NIR, and Raman spectroscopy have proven highly effective for the rapid screening of beverages. For instance, spectroscopic profiling can rapidly discriminate between coffee varieties (Arabica vs. Robusta) and detect common bulk adulterants like chicory or roasted cereals. As supply chains modernize, the future of beverage authentication lies in coupling these post-harvest spectral fingerprints with AI-driven digital platforms. Emerging concepts such as “digital twins”, which create real-time digital replicas of the supply chain, and blockchain technologies ensure that the analytical data generated at the winery or roastery remains secure, immutable, and accessible to the consumer [147].

6.4. Cereals, Fruits, and Vegetables

For plant-based commodities, the focus of authentication is twofold: verifying geographical origin (especially for products with Protected Designation of Origin status) and ensuring that agricultural practices align with specific label claims, such as “organic” or “sustainably farmed.”

Spectroscopic tools are highly versatile for the non-destructive quality assessment of intact fruits and vegetables. Cruz et al. [148] successfully utilized Visible-Near Infrared (VIS-NIR) diffuse reflectance spectroscopy coupled with chemometrics to accurately classify different apple varieties, demonstrating the technique's utility for rapid sorting in packing houses. Expanding on this concept, Sanchez et al. (2024) [149] applied VIS-NIR spectroscopy combined with advanced Machine Learning and Deep Learning algorithms to classify specific apple growing regions, demonstrating that spectral fingerprints contain embedded geographical information that deep learning networks can effectively extract.

To verify agricultural practices, isotopic analysis remains unparalleled. The $\delta^{15}\text{N}$ signature of plant tissues is widely recognized as the most robust marker for distinguishing organically grown crops from conventionally grown ones, as synthetic fertilizers exhibit distinctly different nitrogen isotope ratios from organic manures and composts [94]. For example, Ioannou-Papayianni et al. [91] utilized a combination of isotopic and elemental markers to definitively enhance the authenticity verification of potatoes, linking the tubers directly to their specific soil chemistry and fertilizer regimes. By integrating these post-harvest isotopic and spectral measurements with pre-harvest IoT smart farming data, such as continuous soil moisture, localized weather patterns, and precise fertilizer application logs, stakeholders can build a comprehensive, multi-layered traceability matrix that is remarkably resistant to fraud.

6.5. Meat and Dairy Products

The authentication of animal-derived products presents unique analytical challenges because the isotopic and chemical signatures of meat and dairy are secondary reflections of the animal's diet, drinking water, and local environment [18]. Ensuring the safety, origin, and specific dietary regimes (e.g., grass-fed, pasture-raised, or specific alpine diets) of these products is critical for consumer trust.

Isotopic analysis is highly effective in verifying the dietary history of livestock. The carbon isotope ratio ($\delta^{13}\text{C}$) of meat or milk fat can easily differentiate between animals fed a diet dominated by C3 plants (such as temperate grasses and alfalfa) versus those fed C4 plants (like maize), which is the foundation for verifying “100% grass-fed” claims [18]. Similarly, the oxygen and hydrogen isotopic ratios of milk water provide a direct link to the geographical altitude and latitude where the animal was raised, supporting the authentication of premium alpine cheeses and regional butters.

Animal-derived foods illustrate especially well how pre-harvest conditions can leave measurable signatures in the final product. Feed composition, water source, animal management, and environmental context all influence the isotopic and biochemical profile of milk and meat, creating a chain of evidence that can be followed from farm to fork. Figure 3 captures this idea in a clear visual form, linking the initial agricultural conditions to the analytical signals later measured with portable infrared (NIR) or Raman tools. The result is a useful reminder that authentication is not only about detecting fraud after the fact, but also about preserving a transparent record of how the product was produced.

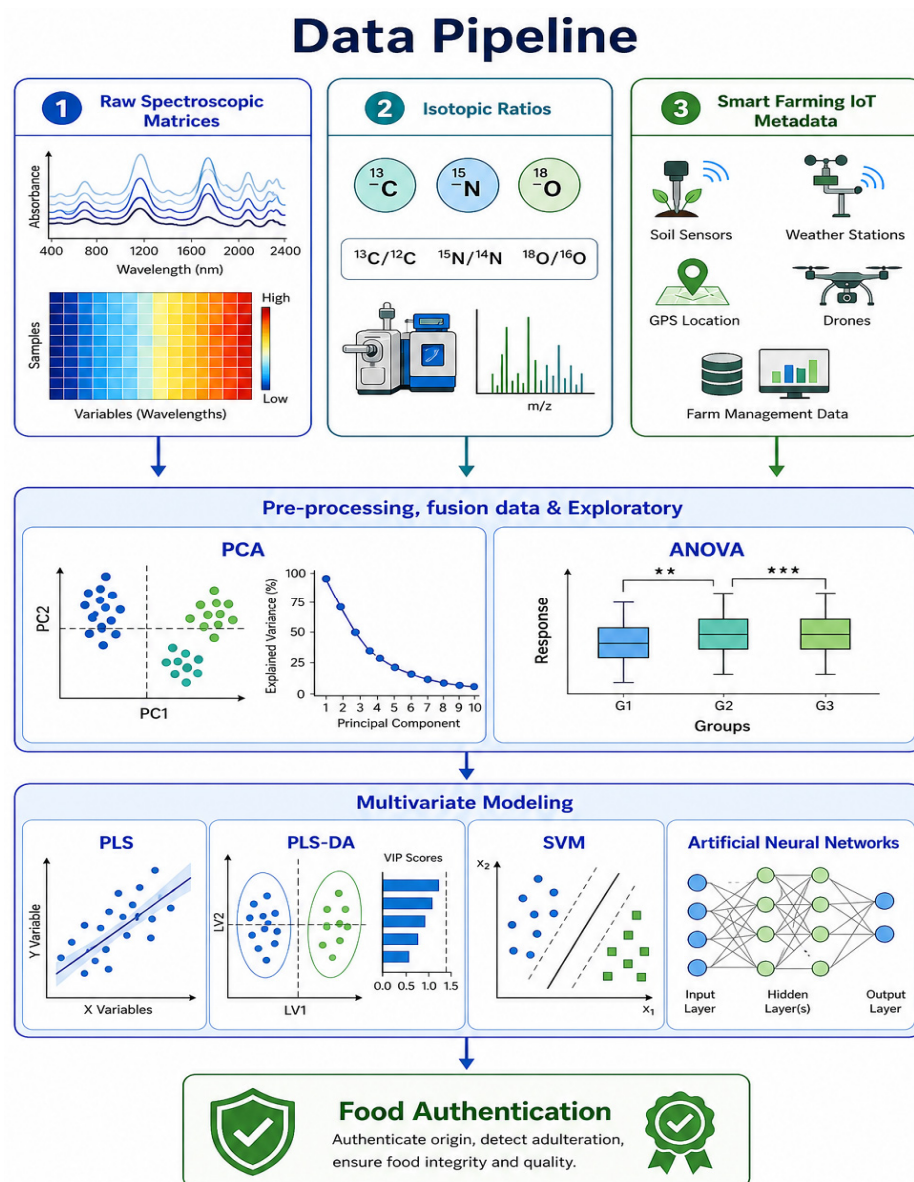


Figure 3. Data pipeline for food authentication based on the integration of spectroscopic matrices, isotopic ratios, and smart farming IoT metadata, followed by pre-processing, exploratory analysis,

multivariate modeling, and final authentication decision-making. In the ANOVA plot, asterisks denote statistical significance levels ($** p < 0.01$, $*** pp < 0.001$). In the SVM diagram, the solid line indicates the decision boundary and dashed lines represent the margins. Ellipses and dashed lines in the Artificial Neural Networks schematic are standard visual conventions used to denote additional hidden nodes and layers.

Spectroscopic techniques are concurrently transforming quality control in the dairy industry. Tarapoulouzi, Jia, and Koidis [143] recently reviewed the new developments and future challenges of deploying non-destructive NIR spectroscopy sensors directly within the cheese industry, highlighting the transition from laboratory analysis to at-line process monitoring. In a practical application of this concept, Tarapoulouzi, Entrenas, et al. [150] conducted a pioneering study using NIR spectroscopy and chemometrics to determine seasonal variations in Halloumi cheese, proving that spectral data can capture the subtle, diet-induced compositional shifts that occur in milk throughout the changing agricultural seasons.

Finally, the safety tracking of complex food matrices is being addressed by highly sensitive, miniaturized analytical techniques. For instance, Tarapoulouzi, Stavrou, et al. [143] developed a green analytical method using Surface-Enhanced Raman Spectroscopy (SERS) with gold nanoparticles on titanium oxide nanowires for the rapid detection of acrylamide (a hazardous processing contaminant). This demonstrates how advanced spectroscopic nanomaterials can be utilized not just for origin authentication (Figure 4), but for the crucial monitoring of food safety parameters at trace levels across the farm-to-fork continuum (Figure 5).

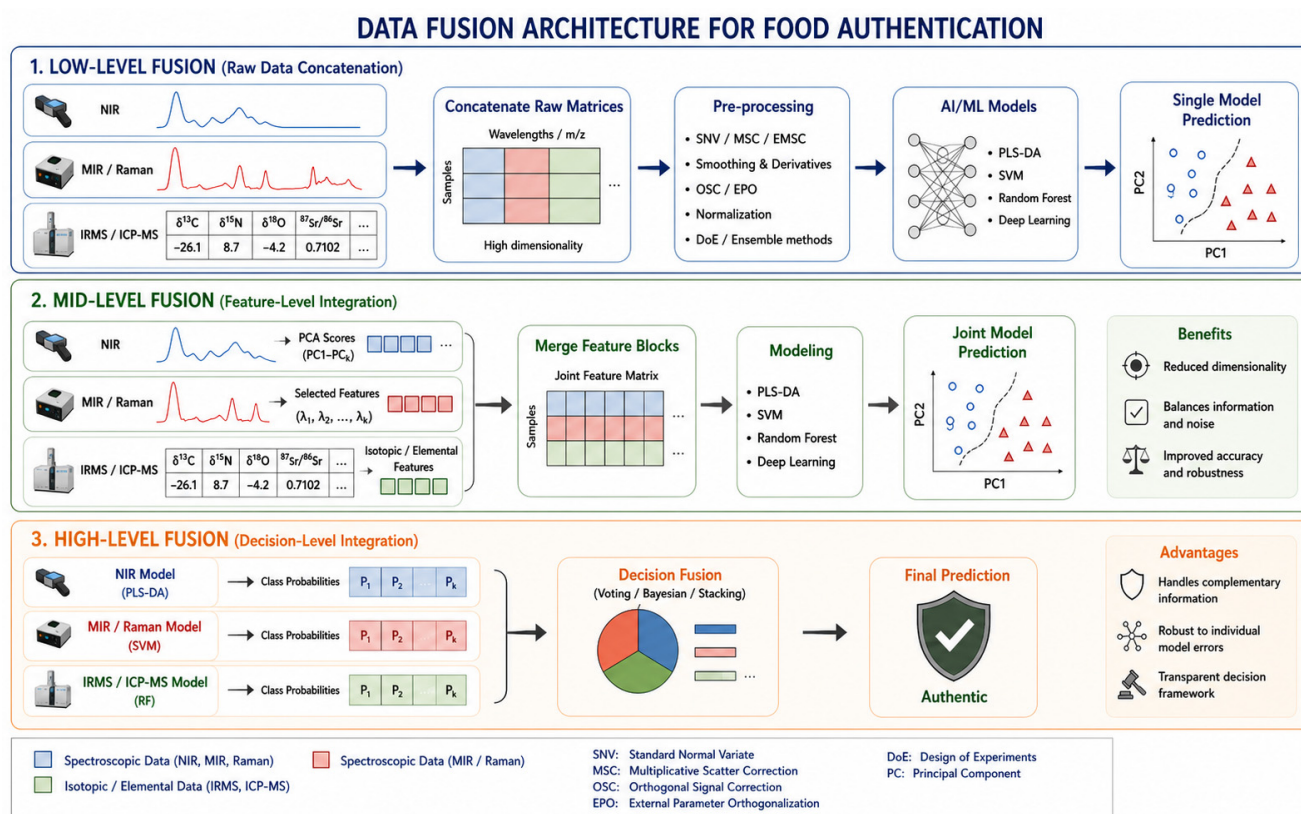


Figure 4. Data fusion architecture for food authentication. The diagram illustrates low-level, mid-level, and high-level integration of spectroscopic (NIR, MIR, Raman) and isotopic/elemental (IRMS, ICP-MS) data. In the predictive modeling plots (PC1 vs. PC2), blue circles and red triangles denote distinct sample classes (e.g., authentic versus adulterated, or different geographical origins), while the dashed line represents the decision boundary separating these classes.

The Isotopic and Spectral Journey of an Animal Product

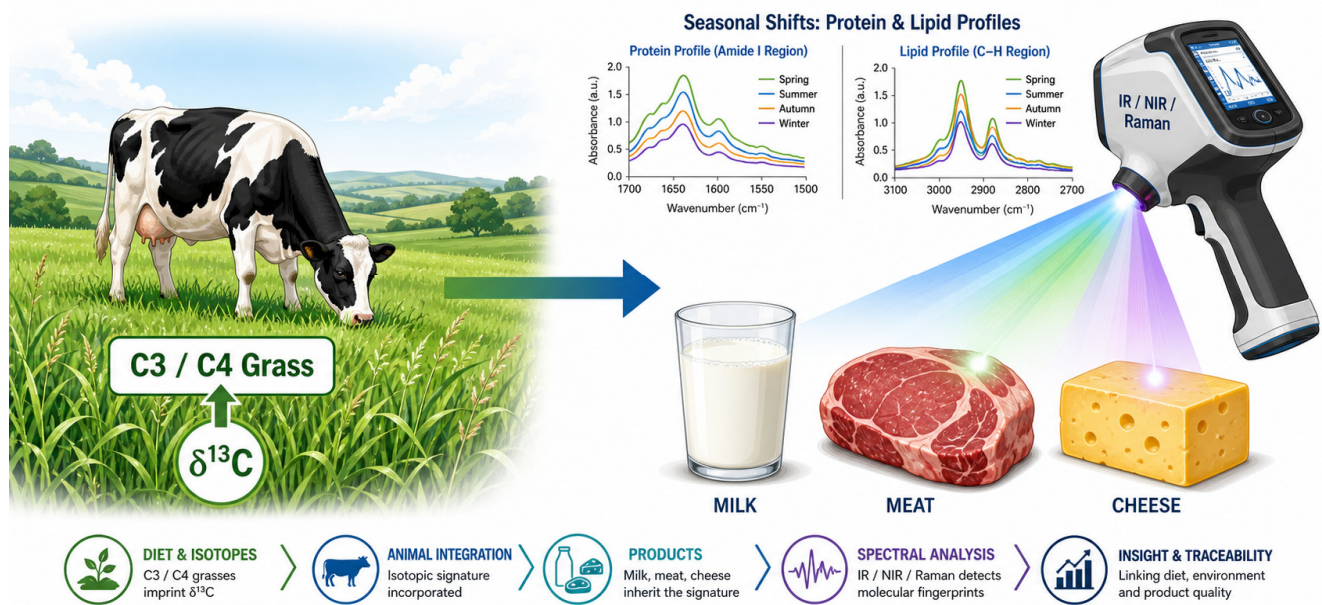


Figure 5. Farm-to-fork analytical tracking of dairy and meat products. The diagram illustrates how initial environmental factors, such as the isotopic signatures ($\delta^{13}\text{C}$) of C3 and C4 grasses, translate into measurable shifts in the protein and lipid profiles of final products, which can be subsequently verified using portable IR, NIR, or Raman spectroscopy.

7. Challenges and Future Perspectives

The implementation of AI in agricultural monitoring and food quality assessment faces three fundamental challenges. First, the performance and accuracy of AI systems depend strongly on the availability of datasets for model training and those must be high-quality and well-annotated. However, data scarcity and the complexity of annotation often arise due to the labor-intensive nature of manual labelling, the high variability in fruit phenotypes, and the rarity or diversity of food fraud cases. A potential solution is data augmentation through the generation of synthetic datasets and hybrid datasets combining real and synthetic data.

Second, model fragility remains a major limitation under real-world conditions. Environmental variability (e.g., lighting changes and occlusions), fruit heterogeneity (e.g., cultivar and maturity differences), low prevalence of certain fraud scenarios, non-ideal instrument design, and the complex optical and chemical properties of highly scattering food materials can all reduce the robustness and generalizability of HSI and RGB-based systems. To address these challenges, multimodal data fusion integrating HSI with complementary imaging modalities, together with domain adaptation techniques, can improve robustness and reduce sensor-to-sensor variability across acquisition conditions. Furthermore, incorporating physical understanding into instrument design can enhance measurement stability and the reliability of multivariate prediction models, as demonstrated by Thorvald II in Figure 6, an agricultural robot for pre-harvest strawberry assessment [151,152]. Subsequently, agricultural robots combining hyperspectral imaging, computer vision, and AI analytics can therefore provide more accurate and consistent real-time evaluation of fruit ripeness, defects, and nutritional quality than traditional manual inspection.

Third, real-time deployment is still challenging due to the high computational demands of deep learning models and the limited latency and energy capacity of edge devices. Lightweight edge AI architectures, combined with model compression techniques such as pruning and quantization, and deployment on hardware-accelerated platforms, can

enable efficient real-time inference [153]. In addition, heterogeneous robotic swarms offer scalable and cost-effective solutions for orchard fruit quality monitoring across diverse crops and environmental conditions while maintaining high throughput and operational reliability [3].



Figure 6. Demonstration of on-site testing with Thorvald II, during a training visit of Dr. Maria Tarapoulouzi to Norwegian University of Life Sciences (NMBU), As, Oslo, Norway.

Ethical implementation in food authentication requires transparency, data protection, accessibility, environmental sustainability, regulatory compliance, and stakeholder engagement. Authentication systems should avoid disadvantaging small producers, minimize social and economic inequalities, and consider long-term societal impacts, including employment and market changes. Because food safety and authenticity involve multiple stakeholders with differing priorities, ethical decision-making must balance fairness, public health, cost-efficiency, and hazard detection. Modern food systems are shaped by interconnected legal, economic, technical, social, and ethical factors, making interdisciplinary collaboration essential. In this context, AI-driven technologies and blockchain-enabled traceability systems can significantly enhance food safety, quality assessment, diagnostic capabilities, production efficiency, and resource management when applied responsibly and sustainably [1,24].

Food analysis is entering a transformative phase enabled by advances in AI models and agri-robotics, offering improved precision and efficiency in food science, which is critical for food safety and quality assurance [1,154]. The development and deployment of explainable artificial intelligence (XAI) frameworks facilitate the interpretation of transparent AI-based quality prediction models, enabling users and stakeholders to better understand their internal decision-making processes [136,137]. In contrast, the widespread use of AI systems operating as “black boxes” has raised concerns regarding transparency and trustworthiness. In this context, XAI can serve as an effective solution to improve user confidence and address public concerns regarding model interpretability [135,155].

In the future, AI applications in food detection and traceability are expected to overcome current limitations and enable more intelligent industrial systems. Building comprehensive, high-quality food databases that reflect diverse regions and conditions, together

with transfer learning and unsupervised domain adaptation, can reduce data heterogeneity and improve model transferability across platforms. At the same time, integrating blockchain and IoT technologies through improved distributed computing and more reliable data acquisition will support real-time, end-to-end supply chain monitoring. Privacy-preserving approaches such as federated learning will further enable secure collaboration in food traceability within bioinformatics-driven systems. AI systems enhanced with adaptive learning and automated optimization will progressively improve performance in complex food environments, supporting the shift toward Food Industry 4.0, where real-time AI monitoring, IoT-enabled sensing, and blockchain-secured data infrastructures operate together. These developments are expected to enhance efficiency, reliability, and sustainability while strengthening global food safety and transforming quality control into a more intelligent and innovative process [24].

Future research should focus on (i) explainable AI (XAI) to improve the interpretability of decision-making processes, (ii) federated learning frameworks that support collaborative model development across supply chains without centralized data sharing, and (iii) the integration of agri-robotics in precision agriculture to mitigate labor shortages. Although AI has significant potential for food quality assurance, its successful implementation will require strong interdisciplinary collaboration among computer scientists, food engineers, and policymakers to ensure both technological innovation and practical applicability. Authentication frameworks should therefore be designed with inclusivity and proportionality in mind, ensuring that small and traditional producers are not inadvertently marginalized by costly digital requirements. Regulatory acceptance will also depend on greater cross-border harmonization of legal and regulatory frameworks, as current requirements vary substantially across jurisdictions, reflecting differences in legislation, cultural practices, and attitudes toward food data privacy [3].

Over the next 5–10 years, technologies such as portable NIR, low-field benchtop NMR, and blockchain in PDO traceability possess sufficient maturity to become mainstream industrial standards. Conversely, technologies like portable laser IRMS, digital twins at commercial scale, and federated learning across real agri-food networks still require rigorous validation under field conditions before widespread adoption [3].

8. Conclusions

The landscape of food authentication is undergoing a fundamental paradigm shift, transitioning from isolated post-harvest analyses to continuous, data-driven, farm-to-fork traceability frameworks. By integrating smart farming technologies with advanced isotopic and spectroscopic analytics, it is now possible to capture the complete agronomic and environmental continuum that shapes a food product's chemical fingerprint. This synergy creates a multidimensional evidence base that is significantly more robust against sophisticated food fraud than any single analytical methodology.

At the core of this transformation is the construction of a comprehensive terroir baseline. High-resolution pre-harvest data, derived from IoT field sensors, remote sensing, and digital farm records, capture the specific environmental and physiological conditions under which a crop is cultivated. When these pre-harvest metrics are fused with post-harvest spectroscopic profiles (such as NIR, MIR, Raman, and NMR) and stable isotope ratios, advanced chemometrics and machine learning models can achieve unprecedented discriminatory power. This multi-block data fusion is critical for safeguarding high-value, geographically protected (e.g., PDO/PGI), and organic commodities, where authenticity is intrinsically tied to origin and specific agricultural practices.

Despite these compelling advances, realizing the full potential of this integrated architecture requires overcoming substantial technical and systemic barriers. The scientific

community and industry stakeholders must address critical challenges regarding cross-platform data interoperability, the standardization of global isotopic and spectral reference databases, and the rigorous calibration transfer required for miniaturized, field-deployable sensors. Furthermore, translating these high-dimensional analytical frameworks into officially recognized regulatory standards remains an ongoing challenge.

Ultimately, the future of food integrity lies in predictive, decentralized, and scalable authentication networks. The convergence of artificial intelligence, agricultural digital twins, and blockchain-enabled ledgers with portable analytical instrumentation will re-define supply chain transparency. Advancing these interdisciplinary frameworks is no longer just a technological objective, but an absolute necessity for safeguarding global food heritage, verifying sustainability claims, and cementing consumer trust in increasingly complex food systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
IoT	Internet of Things
NIR	Near-Infrared Spectroscopy
MIR	Mid-Infrared Spectroscopy
FTIR	Fourier-Transform Infrared Spectroscopy
NMR	Nuclear Magnetic Resonance
IRMS	Isotope Ratio Mass Spectrometry
PLS-DA	Partial Least Squares Discriminant Analysis
PCA	Principal Component Analysis
SVM	Support Vector Machine
UAV	Unmanned Aerial Vehicle
PDO	Protected Designation of Origin
PGI	Protected Geographical Indication
FMIS	Farm Management Information System
MB-PLS	Multi-Block Partial Least Squares
SO-PLS	Sequential and Orthogonalized Partial Least Squares

References

1. Bhat, M.A.; Rather, M.Y.; Singh, P.; Hassan, S.; Hussain, N. Advances in Smart Food Authentication for Enhanced Safety and Quality. *Trends Food Sci. Technol.* **2025**, *155*, 104800. [[CrossRef](#)]
2. Tarapoulouzi, M.; Agriopoulou, S.; Artemi, A. Quality Schemes and Geographical Indicators in the Cheese Agribusiness and the Case of the Cypriot Traditional Cheese Halloumi. In *Agribusiness Innovation and Contextual Evolution, Volume I*; Galati, A., Fiore, M., Thrassou, A., Vrontis, D., Eds.; Springer International Publishing: Cham, Switzerland, 2024; pp. 155–182.

3. Fu, Y.; Sun, D.-W. Advancing Fruit Quality Monitoring with Artificial Intelligence-Augmented Non-Destructive Technologies. *Food Eng. Rev.* **2026**, *18*, 9. [\[CrossRef\]](#)
4. Visconti, P.; De Fazio, R.; Velázquez, R.; Del-Valle-Soto, C.; Giannoccaro, N.I. Development of Sensors-Based Agri-Food Traceability System Remotely Managed by a Software Platform for Optimized Farm Management. *Sensors* **2020**, *20*, 3632. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Grimstad, L.; From, P. The Thorvald II Agricultural Robotic System. *Robotics* **2017**, *6*, 24. [\[CrossRef\]](#)
6. Damak, F.; Bougi, M.S.M.; Araoka, D.; Baba, K.; Furuya, M.; Ksibi, M.; Tamura, K. Soil Geochemistry, Edaphic and Climatic Characteristics as Components of Tunisian Olive Terroirs: Relationship with the Multielemental Composition of Olive Oils for Their Geographical Traceability. *Euro-Mediterr. J. Env. Integr.* **2021**, *6*, 37. [\[CrossRef\]](#)
7. Laureano, G.; Cruz-Silva, A.; Da Silva, J.M.; Oliveira, N.; Duarte, B.; Figueiredo, A. Uncovering Terroir Identity through Elemental Fingerprinting at an Organic Douro Valley Vineyard. *J. Food Compos. Anal.* **2026**, *149*, 108810. [\[CrossRef\]](#)
8. Danezis, G.P.; Tsagkaris, A.S.; Camin, F.; Brusic, V.; Georgiou, C.A. Food Authentication: Techniques, Trends & Emerging Approaches. *TrAC Trends Anal. Chem.* **2016**, *85*, 123–132. [\[CrossRef\]](#)
9. Lohumi, S.; Lee, S.; Lee, H.; Cho, B.-K. A Review of Vibrational Spectroscopic Techniques for the Detection of Food Authenticity and Adulteration. *Trends Food Sci. Technol.* **2015**, *46*, 85–98. [\[CrossRef\]](#)
10. Tarapoulouzi, M.; Pashalidis, I.; Theocharis, C.R. Use of Chemometrics for the Authentication, Characterization and Detection of Adulteration of Cypriot Products Registered Under EU Quality Schemes: A Review. *Chemosensors* **2025**, *13*, 332. [\[CrossRef\]](#)
11. Beć, K.B.; Grabska, J.; Huck, C.W. Miniaturized NIR Spectroscopy in Food Analysis and Quality Control: Promises, Challenges, and Perspectives. *Foods* **2022**, *11*, 1465. [\[CrossRef\]](#) [\[PubMed\]](#)
12. He, H.-J.; Da Silva Ferreira, M.V.; Wu, Q.; Karami, H.; Kamruzzaman, M. Portable and Miniature Sensors in Supply Chain for Food Authentication: A Review. *Crit. Rev. Food Sci. Nutr.* **2025**, *65*, 3966–3986. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Fernando, I.; Fei, J.; Cahoon, S.; Close, D.C. A Review of the Emerging Technologies and Systems to Mitigate Food Fraud in Supply Chains. *Crit. Rev. Food Sci. Nutr.* **2025**, *65*, 5108–5135. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Peladarinos, N.; Piromalis, D.; Cheimaras, V.; Tserepas, E.; Munteanu, R.A.; Papageorgas, P. Enhancing Smart Agriculture by Implementing Digital Twins: A Comprehensive Review. *Sensors* **2023**, *23*, 7128. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Kalaany, C.M.A.; Kimaita, H.N.; Abdelmoneim, A.A.; Khadra, R.; Derardja, B.; Dragonetti, G. The Potential of Low-Cost IoT-Enabled Agrometeorological Stations: A Systematic Review. *Sensors* **2025**, *25*, 6020. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Chalk, P.M.; Inácio, C.T.; Chen, D. An Overview of Contemporary Advances in the Usage of ^{15}N Natural Abundance ($\delta^{15}\text{N}$) as a Tracer of Agro-Ecosystem N Cycle Processes That Impact the Environment. *Agric. Ecosyst. Environ.* **2019**, *283*, 106570. [\[CrossRef\]](#)
17. Corwin, D.L.; Lesch, S.M. Apparent Soil Electrical Conductivity Measurements in Agriculture. *Comput. Electron. Agric.* **2005**, *46*, 11–43. [\[CrossRef\]](#)
18. Camin, F.; Boner, M.; Bontempo, L.; Fahl-Hassek, C.; Kelly, S.D.; Riedl, J.; Rossmann, A. Stable Isotope Techniques for Verifying the Declared Geographical Origin of Food in Legal Cases. *Trends Food Sci. Technol.* **2017**, *61*, 176–187. [\[CrossRef\]](#)
19. González-Domínguez, R.; Sayago, A.; Fernández-Recamales, Á. An Overview on the Application of Chemometrics Tools in Food Authenticity and Traceability. *Foods* **2022**, *11*, 3940. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Hong, Y.; Birse, N.; Quinn, B.; Li, Y.; Jia, W.; McCarron, P.; Wu, D.; Da Silva, G.R.; Vanhaecke, L.; Van Ruth, S.; et al. Data Fusion and Multivariate Analysis for Food Authenticity Analysis. *Nat. Commun.* **2023**, *14*, 3309. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Skidmore, A.K.; Siegenthaler, A.; Wang, T.; Darvishzadeh, R.; Zhu, X.; Chariton, A.; Arjen De Groot, G. Mapping the Relative Abundance of Soil Microbiome Biodiversity from eDNA and Remote Sensing. *Sci. Remote Sens.* **2022**, *6*, 100065. [\[CrossRef\]](#)
22. Biancolillo, A.; Mâge, I.; Næs, T. Combining SO-PLS and Linear Discriminant Analysis for Multi-Block Classification. *Chemom. Intell. Lab. Syst.* **2015**, *141*, 58–67. [\[CrossRef\]](#)
23. Pal, T.; Bommiseti, V.; Suvarnakanti, P.; Dudala, S.S.; Asha, S.; Jaiswal, V. The Revolutionary Role of Blockchain Technology in the Agri-Food Sector Focusing on the Food Supply Chain. *Food Rev. Int.* **2025**, *41*, 770–801. [\[CrossRef\]](#)
24. Liu, Z.; Yu, X.; Liu, N.; Liu, C.; Jiang, A.; Chen, L. Integrating AI with Detection Methods, IoT, and Blockchain to Achieve Food Authenticity and Traceability from Farm-to-Table. *Trends Food Sci. Technol.* **2025**, *158*, 104925. [\[CrossRef\]](#)
25. Bayen, S.; Elliott, C.; Arlorio, M.; Ballin, N.Z.; Birse, N.; Brockmeyer, J.; Chahal, S.; Corradini, M.G.; Hanner, R.; Hann, S.; et al. Towards a Harmonized Approach for Food Authenticity Marker Validation and Accreditation. *Trends Food Sci. Technol.* **2024**, *149*, 104550. [\[CrossRef\]](#)
26. Dhillon, R.; Moncur, Q. Small-Scale Farming: A Review of Challenges and Potential Opportunities Offered by Technological Advancements. *Sustainability* **2023**, *15*, 15478. [\[CrossRef\]](#)
27. Soussi, A.; Zero, E.; Sacile, R.; Trincherio, D.; Fossa, M. Smart Sensors and Smart Data for Precision Agriculture: A Review. *Sensors* **2024**, *24*, 2647. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Garg, D.; Alam, M. Smart Agriculture: A Literature Review. *J. Manag. Anal.* **2023**, *10*, 359–415. [\[CrossRef\]](#)
29. Ariza-Sentís, M.; Vélez, S.; Martínez-Peña, R.; Baja, H.; Valente, J. Object Detection and Tracking in Precision Farming: A Systematic Review. *Comput. Electron. Agric.* **2024**, *219*, 108757. [\[CrossRef\]](#)

30. Assimakopoulos, F.; Vassilakis, C.; Margaritis, D.; Kotis, K.; Spiliotopoulos, D. The Implementation of “Smart” Technologies in the Agricultural Sector: A Review. *Information* **2024**, *15*, 466. [\[CrossRef\]](#)
31. Camin, F.; Larcher, R.; Perini, M.; Bontempo, L.; Bertoldi, D.; Gagliano, G.; Nicolini, G.; Versini, G. Characterisation of Authentic Italian Extra-Virgin Olive Oils by Stable Isotope Ratios of C, O and H and Mineral Composition. *Food Chem.* **2010**, *118*, 901–909. [\[CrossRef\]](#)
32. Zhao, J.; Yu, Y.; Lu, S.; Huang, Y.; Dong, H.; Li, Z. Spectral Data Fusion Combined with Lightweight Convolutional Neural Networks for Lotus Seeds Geographical Origin Identification. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2026**, *358*, 127863. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Zhong, Y.; Li, J.; Liu, H.; Wang, Y. Identification of the Geographical Indication Origin of Gastrodia Elata Blume Based on FT-NIR Spectroscopy. *Infrared Phys. Technol.* **2025**, *151*, 106150. [\[CrossRef\]](#)
34. Li, P.; Liu, H.; Liu, D.; Han, L.; Li, C. Geographical Origin Identification of Rhizoma Atractylodis Macrocephalae Using Hyperspectral Imaging Combined with Broad Learning System and SHapley Additive exPlanations. *Chemosensors* **2025**, *13*, 400. [\[CrossRef\]](#)
35. Stefanis, C.; Giorgi, E.; Tselemonis, G.; Voidarou, C.; Skoufos, I.; Tzora, A.; Tsigalou, C.; Kourkoutas, Y.; Constantinidis, T.C.; Bezirtzoglou, E. Terroir in View of Bibliometrics. *Stats* **2023**, *6*, 956–979. [\[CrossRef\]](#)
36. Radogna, A.V.; Latino, M.E.; Menegoli, M.; Prontera, C.T.; Morgante, G.; Mongelli, D.; Giampetruzzi, L.; Corallo, A.; Bondavalli, A.; Francioso, L. A Monitoring Framework with Integrated Sensing Technologies for Enhanced Food Safety and Traceability. *Sensors* **2022**, *22*, 6509. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Cravero, A.; Pardo, S.; Sepúlveda, S.; Muñoz, L. Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review. *Agronomy* **2022**, *12*, 748. [\[CrossRef\]](#)
38. Adamchuk, V.I.; Hummel, J.W.; Morgan, M.T.; Upadhyaya, S.K. On-the-Go Soil Sensors for Precision Agriculture. *Comput. Electron. Agric.* **2004**, *44*, 71–91. [\[CrossRef\]](#)
39. Rossel, R.V.; Adamchuk, V.I.; Sudduth, K.A.; McKenzie, N.J.; Lobsey, C. Proximal Soil Sensing: An Effective Approach for Soil Measurements in Space and Time. *Adv. Agron.* **2011**, *113*, 243–291. [\[CrossRef\]](#)
40. Bateman, A.S.; Kelly, S.D. Fertilizer Nitrogen Isotope Signatures. *Isot. Environ. Health Stud.* **2007**, *43*, 237–247. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Aceto, M.; Bonello, F.; Musso, D.; Tsolakis, C.; Cassino, C.; Osella, D. Wine Traceability with Rare Earth Elements. *Beverages* **2018**, *4*, 23. [\[CrossRef\]](#)
42. Kelly, S.; Heaton, K.; Hoogewerff, J. Tracing the Geographical Origin of Food: The Application of Multi-Element and Multi-Isotope Analysis. *Trends Food Sci. Technol.* **2005**, *16*, 555–567. [\[CrossRef\]](#)
43. Le, M.T.; Dang, P.-A.T.; Le, C.Y.; Nguyen, T.T.T. Integrating Local Fine Food Traceability Mapping in Vietnam’s Fine Dining Sector. *Appl. Food Res.* **2025**, *5*, 101069. [\[CrossRef\]](#)
44. Hachisuca, A.M.M.; De Souza, E.G.; Oliveira, W.K.M.; Bazzi, C.L.; Donato, D.G.; Mendes, I.D.S.; Abdala, M.C.; Mercante, E. AgDataBox-IoT—Application Development for Agrometeorological Stations in Smart. *MethodsX* **2023**, *11*, 102419. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Cueni, F.; Nelson, D.B.; Boner, M.; Kahmen, A. Using Plant Physiological Stable Oxygen Isotope Models to Counter Food Fraud. *Sci. Rep.* **2021**, *11*, 17314. [\[CrossRef\]](#) [\[PubMed\]](#)
46. Cernusak, L.A.; Barbeta, A.; Bush, R.T.; Eichstaedt, R.; Ferrio, J.P.; Flanagan, L.B.; Gessler, A.; Martín-Gómez, P.; Hirl, R.T.; Kahmen, A.; et al. Do² H and ¹⁸ O in Leaf Water Reflect Environmental Drivers Differently? *New Phytol.* **2022**, *235*, 41–51. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Chahem, L.; Sun, Y.; Amelung, W.; Bauke, S.L. Water-Use Efficiency—Indications from Carbon and Oxygen Stable Isotope Composition of Crop Plants. *Plant Soil* **2025**, *515*, 77–108. [\[CrossRef\]](#)
48. Yang, X.; Chen, J.; Lu, X.; Liu, H.; Liu, Y.; Bai, X.; Qian, L.; Zhang, Z. Advances in UAV Remote Sensing for Monitoring Crop Water and Nutrient Status: Modeling Methods, Influencing Factors, and Challenges. *Plants* **2025**, *14*, 2544. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Sharma, H.; Sidhu, H.; Bhowmik, A. Remote Sensing Using Unmanned Aerial Vehicles for Water Stress Detection: A Review Focusing on Specialty Crops. *Drones* **2025**, *9*, 241. [\[CrossRef\]](#)
50. Vera-Esmeraldas, A.; Pizarro-Oteíza, S.; Labbé, M.; Rojo, F.; Salazar, F. UAV-Based Spectral and Thermal Indices in Precision Viticulture: A Review of NDVI, NDRE, SAVI, GNDVI, and CWSI. *Agronomy* **2025**, *15*, 2569. [\[CrossRef\]](#)
51. Kapari, M.; Sibanda, M.; Magidi, J.; Mabhaudhi, T.; Mpandeli, S.; Nhamo, L. Assessment of the Maize Crop Water Stress Index (CWSI) Using Drone-Acquired Data Across Different Phenological Stages. *Drones* **2025**, *9*, 192. [\[CrossRef\]](#)
52. Park, M.; Somborn, A.; Schlehuber, D.; Keuter, V.; Deerberg, G. Raman Spectroscopy in Crop Quality Assessment: Focusing on Sensing Secondary Metabolites: A Review. *Hortic. Res.* **2023**, *10*, uhad074. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Song, Z.; Xu, C.; Luan, Q.; Li, Y. Multitemporal UAV Study of Phenolic Compounds in Slash Pine Canopies. *Remote Sens. Environ.* **2024**, *315*, 114454. [\[CrossRef\]](#)

54. Castrillo, D.; Blanco, P.; Vélez, S. Can Satellite Remote Sensing Assist in the Characterization of Yeasts Related to Biogeographical Origin? *Sensors* **2023**, *23*, 2059. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Radočaj, D.; Plaščak, I.; Jurišić, M. Global Navigation Satellite Systems as State-of-the-Art Solutions in Precision Agriculture: A Review of Studies Indexed in the Web of Science. *Agriculture* **2023**, *13*, 1417. [\[CrossRef\]](#)
56. Setiyono, T. Precise Positioning in Nitrogen Fertility Sensing in Maize (*Zea mays* L.). *Sensors* **2024**, *24*, 5322. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Ellahi, R.M.; Wood, L.C.; Bekhit, A.E.-D.A. Blockchain-Based Frameworks for Food Traceability: A Systematic Review. *Foods* **2023**, *12*, 3026. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Nuralkyzy, B.; Wadood, S.A.; Nie, J.; Mei, H.; Shao, S.; Zhang, Y.; Li, C.; Yuan, Y.; Rogers, K.M. Guidelines for Sample Preparation and Stable Isotope Analysis of Food for Traceability Studies. *Food Saf. Health* **2026**, *4*, 299–309. [\[CrossRef\]](#)
59. Zhu, L.; Wu, X.; Yang, S. Application Progress of Stable Isotope Dilution Analysis in Volatile Flavor Analysis of Food. *Crit. Rev. Anal. Chem.* **2026**, *56*, 374–397. [\[CrossRef\]](#) [\[PubMed\]](#)
60. Chaudhary, V.; Kajla, P.; Dewan, A.; Pandiselvam, R.; Socol, C.T.; Maerescu, C.M. Spectroscopic Techniques for Authentication of Animal Origin Foods. *Front. Nutr.* **2022**, *9*, 979205. [\[CrossRef\]](#) [\[PubMed\]](#)
61. Ellis, D.I.; Muhamadali, H.; Haughey, S.A.; Elliott, C.T.; Goodacre, R. Point-and-Shoot: Rapid Quantitative Detection Methods for on-Site Food Fraud Analysis—Moving out of the Laboratory and into the Food Supply Chain. *Anal. Methods* **2015**, *7*, 9401–9414. [\[CrossRef\]](#)
62. Melendreras, C.; Montero, J.; Costa-Fernández, J.M.; Soldado, A.; Ferrero, F.; Linera, F.F.; Villedor, M.; Campo, J.C. Trends in Vibrational Spectroscopy: NIRS and Raman Techniques for Health and Food Safety Control. *Sensors* **2026**, *26*, 989. [\[CrossRef\]](#) [\[PubMed\]](#)
63. Squeo, G.; Cruz, J.; De Angelis, D.; Caponio, F.; Amigo, J.M. Considerations about the Gap between Research in Near-Infrared Spectroscopy and Official Methods and Recommendations of Analysis in Foods. *Curr. Opin. Food Sci.* **2024**, *59*, 101203. [\[CrossRef\]](#)
64. Cozzolino, D. Use of Infrared Spectroscopy for In-Field Measurement and Phenotyping of Plant Properties: Instrumentation, Data Analysis, and Examples. *Appl. Spectrosc. Rev.* **2014**, *49*, 564–584. [\[CrossRef\]](#)
65. Nicolaï, B.M.; Beullens, K.; Bobelyn, E.; Peirs, A.; Saeys, W.; Theron, K.I.; Lammertyn, J. Nondestructive Measurement of Fruit and Vegetable Quality by Means of NIR Spectroscopy: A Review. *Postharvest Biol. Technol.* **2007**, *46*, 99–118. [\[CrossRef\]](#)
66. Williams, P.C.; Norris, K. *Near-Infrared Technology: In the Agricultural and Food Industries*, 2nd ed.; American Association of Cereal Chemists: St. Paul, MN, USA, 2001.
67. Osborne, B.G.; Fearn, T.; Hindle, P.H. *Practical NIR Spectroscopy with Applications in Food and Beverage Analysis*, 2nd ed.; Longman Food Technology; Longman Scientific & Technical: Harlow, UK, 1993.
68. Burns, D.A.; Ciurczak, E.W. (Eds.) *Handbook of Near-Infrared Analysis*; CRC Press: Boca Raton, FL, USA, 2007.
69. Sun, D.; Cruz, J.; Alcalà, M.; Romero Del Castillo, R.; Sans, S.; Casals, J. Near Infrared Spectroscopy Determination of Chemical and Sensory Properties in Tomato. *J. Near Infrared Spectrosc.* **2021**, *29*, 289–300. [\[CrossRef\]](#)
70. Fulladosa, E.; Barnés-Calle, C.; Cruz, J.; Martínez, B.; Giró-Candanedo, M.; Comaposada, J.; Font-i-Furnols, M.; Gou, P. Near Infrared Sensors for the Precise Characterization of Salt Content in Canned Tuna Fish. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2023**, *303*, 123217. [\[CrossRef\]](#) [\[PubMed\]](#)
71. Bauer, R.; Nieuwoudt, H.; Bauer, F.F.; Kossmann, J.; Koch, K.R.; Esbensen, K.H. FTIR Spectroscopy for Grape and Wine Analysis. *Anal. Chem.* **2008**, *80*, 1371–1379. [\[CrossRef\]](#) [\[PubMed\]](#)
72. Hassoun, A.; Mâge, I.; Schmidt, W.F.; Temiz, H.T.; Li, L.; Kim, H.-Y.; Nilsen, H.; Biancolillo, A.; Aït-Kaddour, A.; Sikorski, M.; et al. Fraud in Animal Origin Food Products: Advances in Emerging Spectroscopic Detection Methods over the Past Five Years. *Foods* **2020**, *9*, 1069. [\[CrossRef\]](#) [\[PubMed\]](#)
73. Karoui, R.; Debaerdemaeker, J. A Review of the Analytical Methods Coupled with Chemometric Tools for the Determination of the Quality and Identity of Dairy Products. *Food Chem.* **2007**, *102*, 621–640. [\[CrossRef\]](#)
74. Rohman, A.; Man, Y.B.C. Application of Fourier Transform Infrared Spectroscopy for Authentication of Functional Food Oils. *Appl. Spectrosc. Rev.* **2012**, *47*, 1–13. [\[CrossRef\]](#)
75. Hatzakis, E. Nuclear Magnetic Resonance (NMR) Spectroscopy in Food Science: A Comprehensive Review. *Comp. Rev. Food Sci. Food Safe* **2019**, *18*, 189–220. [\[CrossRef\]](#) [\[PubMed\]](#)
76. Borràs, E.; Ferré, J.; Boqué, R.; Mestres, M.; Aceña, L.; Busto, O. Data Fusion Methodologies for Food and Beverage Authentication and Quality Assessment—A Review. *Anal. Chim. Acta* **2015**, *891*, 1–14. [\[CrossRef\]](#) [\[PubMed\]](#)
77. Qin, J.; Chao, K.; Kim, M.S.; Lu, R.; Burks, T.F. Hyperspectral and Multispectral Imaging for Evaluating Food Safety and Quality. *J. Food Eng.* **2013**, *118*, 157–171. [\[CrossRef\]](#)
78. Qin, J.; Kim, M.S.; Chao, K.; Dhakal, S.; Cho, B.-K.; Lohumi, S.; Mo, C.; Peng, Y.; Huang, M. Advances in Raman Spectroscopy and Imaging Techniques for Quality and Safety Inspection of Horticultural Products. *Postharvest Biol. Technol.* **2019**, *149*, 101–117. [\[CrossRef\]](#)

79. Moe Htet, T.T.; Cruz, J.; Khongkaew, P.; Suwanvecho, C.; Suntornsuk, L.; Nuchtavorn, N.; Limwikrant, W.; Phechkrajang, C. PLS-Regression-Model-Assisted Raman Spectroscopy for Vegetable Oil Classification and Non-Destructive Analysis of Alpha-Tocopherol Contents of Vegetable Oils. *J. Food Compos. Anal.* **2021**, *103*, 104119. [\[CrossRef\]](#)
80. Khongkaew, P.; Phechkrajang, C.; Cruz, J.; Cárdenas, V.; Rojsanga, P. Quantitative Models for Detecting the Presence of Lead in Turmeric Using Raman Spectroscopy. *Chemom. Intell. Lab. Syst.* **2020**, *200*, 103994. [\[CrossRef\]](#)
81. Craig, A.P.; Franca, A.S.; Irudayaraj, J. Surface-Enhanced Raman Spectroscopy Applied to Food Safety. *Annu. Rev. Food Sci. Technol.* **2013**, *4*, 369–380. [\[CrossRef\]](#) [\[PubMed\]](#)
82. Ruoff, K.; Luginbühl, W.; Künzli, R.; Bogdanov, S.; Bosset, J.O.; Von Der Ohe, K.; Von Der Ohe, W.; Amadò, R. Authentication of the Botanical and Geographical Origin of Honey by Front-Face Fluorescence Spectroscopy. *J. Agric. Food Chem.* **2006**, *54*, 6858–6866. [\[CrossRef\]](#) [\[PubMed\]](#)
83. Rateni, G.; Dario, P.; Cavallo, F. Smartphone-Based Food Diagnostic Technologies: A Review. *Sensors* **2017**, *17*, 1453. [\[CrossRef\]](#) [\[PubMed\]](#)
84. Airado-Rodríguez, D.; Durán-Merás, I.; Galeano-Díaz, T.; Wold, J.P. Front-Face Fluorescence Spectroscopy: A New Tool for Control in the Wine Industry. *J. Food Compos. Anal.* **2011**, *24*, 257–264. [\[CrossRef\]](#)
85. Consonni, R.; Cagliani, L.R. NMR Studies on Italian PDO Olive Oils and Their Potential in Olive-Tree-Derived Products Characterization. *Eur. J. Lipid Sci. Technol.* **2019**, *121*, 1800174. [\[CrossRef\]](#)
86. Spraul, M.; Schütz, B.; Rinke, P.; Koswig, S.; Humpfer, E.; Schäfer, H.; Mörtter, M.; Fang, F.; Marx, U.C.; Minoja, A. NMR-Based Multi Parametric Quality Control of Fruit Juices: SGF Profiling. *Nutrients* **2009**, *1*, 148–155. [\[CrossRef\]](#) [\[PubMed\]](#)
87. Bertram, H.C.; Andersen, H.J. NMR and the Water-holding Issue of Pork. *J. Anim. Breed. Genet.* **2007**, *124*, 35–42. [\[CrossRef\]](#) [\[PubMed\]](#)
88. Di Matteo, G.; Grassi, S.; Emanuele, M.C.; Scioli, G.; Brigante, F.I.; Bontempo, L.; Ingallina, C.; Guillou, C.; Sobolev, A.P.; Mannina, L. Current Applications of Benchtop FT-NMR in Food Science: From Quality Control to Adulteration Detection. *Food Res. Int.* **2025**, *209*, 116327. [\[CrossRef\]](#) [\[PubMed\]](#)
89. Pujol, C.; Danoun, S.; Biasini, G.; Retailleau, E.; Masson, J.; Balayssac, S.; Gilard, V. Benchtop NMR Coupled with Chemometrics: A Workflow for Unveiling Hidden Drug Ingredients in Honey-Based Supplements. *Molecules* **2024**, *29*, 2086. [\[CrossRef\]](#) [\[PubMed\]](#)
90. Nasr, E.G.; Epova, E.N.; Barre, J.; Sebilo, M.; De Diego, A.; Souissi, R.; Abderrazak, H.; Donard, O.F.X. Combined Use of $^{87}\text{Sr}/^{86}\text{Sr}$ and Carbon Isotopes with Multielemental Analysis for the Geographical Authentication of Tunisian and European Olive Oils. *Food Chem.* **2023**, *426*, 136487. [\[CrossRef\]](#) [\[PubMed\]](#)
91. Ioannou-Papayianni, E.; Damaskinos, C.; Tarapoulouzi, M.; Louka, C.; Savvidou, C.; Tzoni, E.; Kokkinofa, R. Utilizing Isotopic and Elemental Markers to Enhance the Authenticity of Potatoes. *Eur. Food Res. Technol.* **2025**, *251*, 367–375. [\[CrossRef\]](#)
92. Perini, M.; Bontempo, L. Liquid Chromatography Coupled to Isotope Ratio Mass Spectrometry (LC-IRMS): A Review. *TrAC Trends Anal. Chem.* **2022**, *147*, 116515. [\[CrossRef\]](#)
93. Picó, Y.; Barceló, D. Isotopic Mass Spectrometry in Food and Environmental Chemistry. In *Mass Spectrometry in Food and Environmental Chemistry*; Picó, Y., Campo, J., Eds.; The Handbook of Environmental Chemistry; Springer International Publishing: Cham, Switzerland, 2022; Volume 119, pp. 99–125.
94. Capuano, E.; Boerrigter-Eenling, R.; Van Der Veer, G.; Van Ruth, S.M. Analytical Authentication of Organic Products: An Overview of Markers. *J. Sci. Food Agric.* **2013**, *93*, 12–28. [\[CrossRef\]](#) [\[PubMed\]](#)
95. Gao, F.; Zeng, G.; Hao, X.; Wang, H.; Li, H. Variation and Fractionation of $\delta^2\text{H}$, $\delta^{18}\text{O}$, and $\delta^{17}\text{O}$ Stable Isotopes from Irrigation Water to Soil, Grapes, and Wine for the Traceability of Geographical Origins. *Food Chem.* **2025**, *462*, 141012. [\[CrossRef\]](#) [\[PubMed\]](#)
96. Terro, C.; Modic, R.; Ogrinc, M.; Simčič, A.; Drole, J.; Eftimov, T.; Koroušić Seljak, B.; Ogrinc, N. IsoFoodTrack: A Comprehensive Database and Management System Based on Stable Isotope Ratio Analysis for Combating Food Fraud. *Front. Nutr.* **2025**, *12*, 1516521. [\[CrossRef\]](#) [\[PubMed\]](#)
97. Li, A.; Zhao, D.; Li, J.; Qian, J.; Chen, Q.; Qian, X.; Yang, X.; Zhao, J. Authenticating the Geographical Origin of Jingbai Pear in Northern China by Multiple Stable Isotope and Elemental Analysis. *Foods* **2024**, *13*, 3417. [\[CrossRef\]](#) [\[PubMed\]](#)
98. Liu, H.; Nie, J.; Liu, Y.; Wadood, S.A.; Rogers, K.M.; Yuan, Y.; Gan, R.-Y. A Review of Recent Compound-Specific Isotope Analysis Studies Applied to Food Authentication. *Food Chem.* **2023**, *415*, 135791. [\[CrossRef\]](#) [\[PubMed\]](#)
99. San-Emeterio, L.M.; Correa-López, G.; Carrere, D.; González-Pérez, J.A.; Jiménez-Morillo, N.T. The Hidden Isotope Fractionation: How Temperature of Pyrolysis Coupled to Compound-Specific Isotope Analysis Shapes $\delta^{13}\text{C}$ Results. *J. Chromatogr. A* **2026**, *1775*, 466919. [\[CrossRef\]](#) [\[PubMed\]](#)
100. Spangenberg, J.E.; Ogrinc, N. Authentication of Vegetable Oils by Bulk and Molecular Carbon Isotope Analyses with Emphasis on Olive Oil and Pumpkin Seed Oil. *J. Agric. Food Chem.* **2001**, *49*, 1534–1540. [\[CrossRef\]](#) [\[PubMed\]](#)
101. Dehelean, A.; Feher, I.; Romulus, P.; Magdas, D.A.; Covaciu, F.-D.; Kasza, A.M.; Curean, V.; Cristea, G. Influence of Geographical Origin on Isotopic and Elemental Compositions of Pork Meat. *Foods* **2023**, *12*, 4271. [\[CrossRef\]](#) [\[PubMed\]](#)

102. Wang, N.; Wang, C.; Wang, H.; Zhang, L.; Zhang, M.; Jing, H.; Mei, L.; Qiu, S.; Liu, X.; Lv, J.; et al. C, H, O, N Stable Isotope Analysis Coupled with Chemometrics for Geographic Origin Authentication of Pacific White Shrimp (*Litopenaeus vannamei*) in China. *Foods* **2026**, *15*, 1274. [\[CrossRef\]](#) [\[PubMed\]](#)
103. Muñoz-Redondo, J.M.; Bertoldi, D.; Tonon, A.; Ziller, L.; Camin, F.; Moreno-Rojas, J.M. Multi-Element and Stable Isotopes Characterization of Commercial Avocado Fruit (*Persea americana* Mill) with Origin Authentication Purposes. *Food Control* **2022**, *137*, 108975. [\[CrossRef\]](#)
104. Bontempo, L.; Paolini, M.; Franceschi, P.; Ziller, L.; García-González, D.L.; Camin, F. Characterisation and Attempted Differentiation of European and Extra-European Olive Oils Using Stable Isotope Ratio Analysis. *Food Chem.* **2019**, *276*, 782–789. [\[CrossRef\]](#) [\[PubMed\]](#)
105. Tarapoulouzi, M.; Skiada, V.; Agriopoulou, S.; Psomiadis, D.; Rébufa, C.; Roussos, S.; Theocharis, C.R.; Katsaris, P.; Varzakas, T. Chemometric Discrimination of the Geographical Origin of Three Greek Cultivars of Olive Oils by Stable Isotope Ratio Analysis. *Foods* **2021**, *10*, 336. [\[CrossRef\]](#) [\[PubMed\]](#)
106. Ma, Y.; Li, Y.; Shao, F.; Lu, Y.; Meng, W.; Rogers, K.M.; Sun, D.; Wu, H.; Peng, X. Advancing Stable Isotope Analysis for Alcoholic Beverages' Authenticity: Novel Approaches in Fraud Detection and Traceability. *Foods* **2025**, *14*, 943. [\[CrossRef\]](#) [\[PubMed\]](#)
107. Malinovsky, D.; Dunn, P.J.H.; Rooke, P.; Goenaga-Infante, H. The Effect of Roasting on Boron Isotope Ratio in Coffee Beans: Implications for Provenance Studies of Roasted Coffee. *Food Chem.* **2024**, *439*, 138128. [\[CrossRef\]](#) [\[PubMed\]](#)
108. Torres-Cobos, B.; Rosell, M.; Soler, A.; Rovira, M.; Romero, A.; Guardiola, F.; Vichi, S.; Tres, A. A Multi-Isotopic Chemometric Approach for Tracing Hazelnut Origins. *Foods* **2024**, *13*, 3399. [\[CrossRef\]](#) [\[PubMed\]](#)
109. Li, A.; Yang, J.; Ju, Y.; Niu, S.; Liu, S.; Kelly, S.D.; Vlachou, C.; Wang, M. Multiple Stable Isotopes Characterization as a Tool for Determination of the Geographical Origin of Honey in Northern China. *J. Food Compos. Anal.* **2026**, *149*, 108800. [\[CrossRef\]](#)
110. Horacek, M.; Klčova, L.; Hudcovicova, M.; Ondreickova, K.; Gubis, J.; Hölzl, S. Differentiation of Apricots of Different Geographic Origin in Central and Southern Europe by Applying $^{87}\text{Sr}/^{86}\text{Sr}$ Analysis: Potential and Limitations. *Foods* **2022**, *11*, 2239. [\[CrossRef\]](#) [\[PubMed\]](#)
111. Wang, M.; Jiang, Y.; Han, X.; Ren, A.; He, J.; Yin, M.; Zhao, Y.; Peng, H. Fine-Scale Strontium Isotope Mapping in Eastern China (Anhui Province) and Its Application in Food Traceability. *Foods* **2025**, *15*, 33. [\[CrossRef\]](#) [\[PubMed\]](#)
112. Thanasi, V.; Evola, D.; Victorino, G.; Ricardo-da-Silva, J.M.; Madeira, M.; Catarino, S. Effect of the Vintage Year on Strontium Isotopic Ratio ($^{87}\text{Sr}/^{86}\text{Sr}$) of Wines: A Portuguese Case Study. *J. Sci. Food Agric.* **2026**, *106*, 1940–1947. [\[CrossRef\]](#) [\[PubMed\]](#)
113. Crocombe, R.A. Portable Spectroscopy. *Appl. Spectrosc.* **2018**, *72*, 1701–1751. [\[CrossRef\]](#) [\[PubMed\]](#)
114. Giró-Candanedo, M.; Cruz, J.; Comaposada, J.; Barnés-Calle, C.; Gou, P.; Fulladosa, E. Differentiation between Fresh and Frozen-Thawed Mackerel Fish Using Low-Cost Portable near Infrared Spectrometry Devices. *J. Food Eng.* **2024**, *379*, 112131. [\[CrossRef\]](#)
115. Stocco, G.; Molle, A.; Biffani, S.; Pizzamiglio, V.; Cruz, J.; Ferragina, A.; Cipolat-Gotet, C. Use of NDSS to Discriminate between Parmigiano Reggiano and Grana Padano PDO and Their Ripening Times from Grated Cheese Spectra. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2025**, *337*, 126087. [\[CrossRef\]](#) [\[PubMed\]](#)
116. Feudale, R.N.; Woody, N.A.; Tan, H.; Myles, A.J.; Brown, S.D.; Ferré, J. Transfer of Multivariate Calibration Models: A Review. *Chemom. Intell. Lab. Syst.* **2002**, *64*, 181–192. [\[CrossRef\]](#)
117. Mishra, P.; Biancolillo, A.; Roger, J.M.; Marini, F.; Rutledge, D.N. New Data Preprocessing Trends Based on Ensemble of Multiple Preprocessing Techniques. *TrAC Trends Anal. Chem.* **2020**, *132*, 116045. [\[CrossRef\]](#)
118. Wold, S.; Sjöström, M.; Eriksson, L. PLS-Regression: A Basic Tool of Chemometrics. *Chemom. Intell. Lab. Syst.* **2001**, *58*, 109–130. [\[CrossRef\]](#)
119. Mennickent, D.; Rodríguez, A.; Opazo, M.C.; Riedel, C.A.; Castro, E.; Eriz-Salinas, A.; Appel-Rubio, J.; Aguayo, C.; Damiano, A.E.; Guzmán-Gutiérrez, E.; et al. Machine Learning Applied in Maternal and Fetal Health: A Narrative Review Focused on Pregnancy Diseases and Complications. *Front. Endocrinol.* **2023**, *14*, 1130139. [\[CrossRef\]](#) [\[PubMed\]](#)
120. Bhalodia, D.N.; Baria, D.A. A Review on Chemometrics in Pharmaceutical Analysis. *Int. J. Pharm. Sci.* **2024**, *2*, 58–78. [\[CrossRef\]](#)
121. Biancolillo, A.; Marini, F.; Ruckebusch, C.; Vitale, R. Chemometric Strategies for Spectroscopy-Based Food Authentication. *Appl. Sci.* **2020**, *10*, 6544. [\[CrossRef\]](#)
122. Agelet, L.E.; Hurburgh, C.R. A Tutorial on Near Infrared Spectroscopy and Its Calibration. *Crit. Rev. Anal. Chem.* **2010**, *40*, 246–260. [\[CrossRef\]](#)
123. Engel, J.; Gerretzen, J.; Szymańska, E.; Jansen, J.J.; Downey, G.; Blanchet, L.; Buydens, L.M.C. Breaking with Trends in Pre-Processing? *TrAC Trends Anal. Chem.* **2013**, *50*, 96–106. [\[CrossRef\]](#)
124. Rinnan, Å.; Berg, F.V.D.; Engelsen, S.B. Review of the Most Common Pre-Processing Techniques for near-Infrared Spectra. *TrAC Trends Anal. Chem.* **2009**, *28*, 1201–1222. [\[CrossRef\]](#)
125. Martens, H.; Stark, E. Extended Multiplicative Signal Correction and Spectral Interference Subtraction: New Preprocessing Methods for near Infrared Spectroscopy. *J. Pharm. Biomed. Anal.* **1991**, *9*, 625–635. [\[CrossRef\]](#) [\[PubMed\]](#)

126. Dieterle, F.; Ross, A.; Schlotterbeck, G.; Senn, H. Probabilistic Quotient Normalization as Robust Method to Account for Dilution of Complex Biological Mixtures. Application in ¹H NMR Metabonomics. *Anal. Chem.* **2006**, *78*, 4281–4290. [\[CrossRef\]](#) [\[PubMed\]](#)
127. Savitzky, A.; Golay, M.J.E. Smoothing and Differentiation of Data by Simplified Least Squares Procedures. *Anal. Chem.* **1964**, *36*, 1627–1639. [\[CrossRef\]](#)
128. Zimmermann, B.; Kohler, A. Optimizing Savitzky–Golay Parameters for Improving Spectral Resolution and Quantification in Infrared Spectroscopy. *Appl. Spectrosc.* **2013**, *67*, 892–902. [\[CrossRef\]](#) [\[PubMed\]](#)
129. Roger, J.M.; Palagos, B.; Bertrand, D.; Fernandez-Ahumada, E. CovSel: Variable Selection for Highly Multivariate and Multi-Response Calibration. *Chemom. Intell. Lab. Syst.* **2011**, *106*, 216–223. [\[CrossRef\]](#)
130. Drivelos, S.A.; Georgiou, C.A. Multi-Element and Multi-Isotope-Ratio Analysis to Determine the Geographical Origin of Foods in the European Union. *TrAC Trends Anal. Chem.* **2012**, *40*, 38–51. [\[CrossRef\]](#)
131. Bro, R.; Smilde, A.K. Principal Component Analysis. *Anal. Methods* **2014**, *6*, 2812–2831. [\[CrossRef\]](#)
132. Barker, M.; Rayens, W. Partial Least Squares for Discrimination. *J. Chemom.* **2003**, *17*, 166–173. [\[CrossRef\]](#)
133. Blanco, M.; Cruz, J.; Armengol, M. Control Production of Polyester Resins by NIR Spectroscopy. *Microchem. J.* **2008**, *90*, 118–123. [\[CrossRef\]](#)
134. Gullifa, G.; Barone, L.; Papa, E.; Giuffrida, A.; Materazzi, S.; Risoluti, R. Portable NIR Spectroscopy: The Route to Green Analytical Chemistry. *Front. Chem.* **2023**, *11*, 1214825. [\[CrossRef\]](#) [\[PubMed\]](#)
135. Qamar, T.; Bawany, N.Z. Understanding the Black-Box: Towards Interpretable and Reliable Deep Learning Models. *PeerJ Comput. Sci.* **2023**, *9*, e1629. [\[CrossRef\]](#) [\[PubMed\]](#)
136. Adil, M.; Fan, Y.; Xiao, X.; Zou, Y.; Ren, J.; Faisal Manzoor, M. Artificial Intelligence and Machine Learning: Shaping the Future of Food Safety, Quality Control, Traceability Systems, and Nutrition. *Food Rev. Int.* **2026**, *42*, 3802–3833. [\[CrossRef\]](#)
137. Arrighi, L.; De Moraes, I.A.; Zullich, M.; Simonato, M.; Barbin, D.F.; Barbon Junior, S. Explainable Artificial Intelligence Techniques for Interpretation of Food Models: A Review. *Artif. Intell. Rev.* **2026**, *59*, 176. [\[CrossRef\]](#)
138. Stocco, G.; Gómez-Mascaraque, L.G.; Deshwal, G.K.; Sanchez, J.C.; Molle, A.; Pizzamiglio, V.; Berzaghi, P.; Gergov, G.; Cipolat-Gotet, C. Exploring the Use of NIR and Raman Spectroscopy for the Prediction of Quality Traits in PDO Cheeses. *Front. Nutr.* **2024**, *11*, 1327301. [\[CrossRef\]](#) [\[PubMed\]](#)
139. Tagarakis, A.C.; Benos, L.; Kyriakarakos, G.; Pearson, S.; Sørensen, C.G.; Bochtis, D. Digital Twins in Agriculture and Forestry: A Review. *Sensors* **2024**, *24*, 3117. [\[CrossRef\]](#) [\[PubMed\]](#)
140. Escribà-Gelonch, M.; Liang, S.; Van Schalkwyk, P.; Fisk, I.; Long, N.V.D.; Hessel, V. Digital Twins in Agriculture: Orchestration and Applications. *J. Agric. Food Chem.* **2024**, *72*, 10737–10752. [\[CrossRef\]](#) [\[PubMed\]](#)
141. Nasirahmadi, A.; Hensel, O. Toward the Next Generation of Digitalization in Agriculture Based on Digital Twin Paradigm. *Sensors* **2022**, *22*, 498. [\[CrossRef\]](#) [\[PubMed\]](#)
142. Hayes, E.; Greene, D.; O'Donnell, C.; O'Shea, N.; Fenelon, M.A. Spectroscopic Technologies and Data Fusion: Applications for the Dairy Industry. *Front. Nutr.* **2023**, *9*, 1074688. [\[CrossRef\]](#) [\[PubMed\]](#)
143. Tarapoulouzi, M.; Jia, W.; Koidis, A. New Developments and Future Challenges of Non-Destructive Near-Infrared Spectroscopy Sensors in the Cheese Industry. *Sensors* **2026**, *26*, 556. [\[CrossRef\]](#) [\[PubMed\]](#)
144. Junaid, M.; Taib, N.S.; Sukmawati, S.; Zabrina, G. Global Trend of Agricultural Precision for Plant Pathology: Bibliometric Study in Scopus Database. *Wallacea Plant Prot. J.* **2025**, *1*, 19–31. [\[CrossRef\]](#)
145. Mamabolo, E.; Mashala, M.J.; Mugari, E.; Mogale, T.E.; Mathebula, N.; Mabitsela, K.; Ayisi, K.K. Application of Precision Agriculture Technologies for Crop Protection and Soil Health. *Smart Agric. Technol.* **2025**, *12*, 101270. [\[CrossRef\]](#)
146. Devarajan, D.; Allafi, R.; Obayya, M.; Nemri, N. AI Based Real Time Disease Diagnosis in Plants Using Deep Learning Driven CNNs. *Sci. Rep.* **2026**, *16*, 4587. [\[CrossRef\]](#) [\[PubMed\]](#)
147. Verdouw, C.N.; Wolfert, J.; Beulens, A.J.M.; Rialland, A. Virtualization of Food Supply Chains with the Internet of Things. *J. Food Eng.* **2016**, *176*, 128–136. [\[CrossRef\]](#)
148. Cruz, J.; Gergov, G.; Tarapoulouzi, M.; Kirilova, E.; Kostadinova, O.; Nikolova, K. Classification of Apple Varieties by VIS-NIR Diffuse Reflectance Spectroscopy and Chemometrics. *Bulg. Chem. Commun.* **2024**, *56*, 106. [\[CrossRef\]](#)
149. Sanchez, J.C.; Gallo, Y.R.; Tarapoulouzi, M.; Gergov, G.; Nikolova, K.; Cardona, M. Classification of Apple Growing Region by Vis-Near Infrared Spectroscopy Coupled with Machine Learning and Deep Learning Methods. In *2024 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT)*; IEEE: New York, NY, USA, 2024; pp. 44–49.
150. Tarapoulouzi, M.; Entrenas, J.-A.; Pérez-Marín, D.; Pashalidis, I.; Theocharis, C.R. A Preliminary Study on Determining Seasonal Variations in Halloumi Cheese Using Near-Infrared Spectroscopy and Chemometrics. *Processes* **2024**, *12*, 1517. [\[CrossRef\]](#)
151. Vraalstad, V.; Hansen, A.H.; O'Farrell, M.; Tschudi, J.; Wold, J.P. Near-Infrared Interaction Spectroscopy Under Daylight Conditions to Assess Total Soluble Solids in On-the-Plant Strawberries. *Appl. Spectrosc. Pract.* **2026**, *4*, 27551857261443636. [\[CrossRef\]](#)

152. Vraalstad, V.; Tschudi, J.; O'Farrell, M.; Hansen, A.; Wold, J.P. First-Principles Methodology for Developing Robust NIR Spectroscopic Solutions for Real-World Applications. In *Proceedings of the Photonic Technologies in Plant and Agricultural Science II*; Heinemann, D., Polder, G., Eds.; SPIE: San Francisco, CA, USA, 2025; p. 9.
153. El Jarroudi, M.; Kouadio, L.; Delfosse, P.; Bock, C.H.; Mahlein, A.-K.; Fettweis, X.; Mercatoris, B.; Adams, F.; Lenné, J.M.; Hamdioui, S. Leveraging Edge Artificial Intelligence for Sustainable Agriculture. *Nat. Sustain.* **2024**, *7*, 846–854. [[CrossRef](#)]
154. Almoselhy, R.I.M.; Katrandzhiev, N.; Khaled, M.B.; Benchikh, I.; Usmani, A.; Siddiqui, M.A.; Rajendran, R.; Bihani, M.; Thomas, S. Advances in Nondestructive Techniques for Quality and Safety Assessment of Olive Products Using AI and Big Data Analytics: A Systematic Review. *Res. Sq.* **2026**. [[CrossRef](#)] [[PubMed](#)]
155. Sebti, M.R.; McCarthy, U.; Ktenioudaki, A.; Russo, M.; Merenda, M. Traceability and Anti-Counterfeiting in Agri-Food Supply Chains: A Review of RFID, IoT, Blockchain, and AI Technologies. *Sensors* **2026**, *26*, 1685. [[CrossRef](#)] [[PubMed](#)]

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