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*Review*

# Terahertz Sensing for Agricultural Engineering: Applications and Intelligent Data Analysis

**Xiaodong Zhang [1], Deshen Zhang [1], Chuandong Guo [1], Shifang Song [1], Xiangyu Han [1], Zonghua Leng [1] and Yixue Zhang [2,*]**

[1] School of Agricultural Engineering, Jiangsu University, Zhenjiang 212013, China; zxd700227@ujs.edu.cn (X.Z.); 2212516036@stmail.ujs.edu.cn (D.Z.); 2212516044@stmail.ujs.edu.cn (C.G.); 2212516047@stmail.ujs.edu.cn (S.S.); 2212416036@stmail.ujs.edu.cn (X.H.); 2212416037@stmail.ujs.edu.cn (Z.L.)

[2] Basic Engineering Training Center, Jiangsu University, Zhenjiang 212013, China

* Correspondence: 1000005803@ujs.edu.cn

**Abstract**

The growing demand for rapid and nondestructive sensing in precision and smart agriculture, particularly for continuous crop monitoring in controlled environment agriculture (CEA), has stimulated interest in terahertz (THz) technologies. Owing to their sensitivity to water, low-frequency molecular vibrations, and dielectric properties, THz waves provide a promising approach for probing agricultural materials. This review summarizes advances in THz sensing for agricultural engineering. The principles and characteristics of THz time-domain spectroscopy, frequency-domain spectroscopy, and imaging are first introduced, together with the major interaction mechanisms between THz waves and agricultural materials. Advances in THz data analysis are then discussed, focusing on model selection, reliability under small-sample conditions, multi-source information fusion, and mechanism-informed analysis. Applications are subsequently reviewed in seed quality and germplasm identification, soil property assessment and contaminant detection, crop water-status monitoring, stress and disease detection, and agricultural product quality and safety assessment. Key challenges include complex-matrix interference, weak target responses, limited model generalization across scenarios, and system integration. Future research should emphasize high-sensitivity sensing, mechanism-data-integrated modeling, and miniaturized online detection systems to facilitate the practical deployment of THz technologies in agriculture, including greenhouses and other controlled production environments.

**Keywords:** terahertz sensing; terahertz spectroscopy; agricultural engineering; nondestructive sensing; machine learning; multimodal data fusion

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## 1. Introduction

With global population growth, increasing constraints on resources and the environment, and the transition of agricultural production toward precision and intelligent management, there is a growing demand for rapid, continuous, and nondestructive information acquisition technologies in seed quality evaluation, soil environmental monitoring, crop physiological status diagnosis, and agricultural product quality and safety control [1,2]. Conventional physicochemical methods generally rely on manual sampling, sample pretreatment, and laboratory-based instrumental analysis. Although these methods provide relatively high analytical accuracy, they are time-consuming and are difficult to apply to

large-scale, high-frequency, and on-site monitoring [3,4]. Nondestructive sensing technologies, including near-infrared spectroscopy [5], hyperspectral imaging [6], thermal imaging [7], and machine vision [8], have been widely applied to agricultural information acquisition. However, these techniques have different limitations in terms of detection depth, information type, and adaptability to complex samples, and remain insufficient for effectively characterizing certain internal structures, moisture states, and subtle compositional variations [9,10]. Therefore, exploring emerging sensing approaches based on different electromagnetic response mechanisms is important for extending the capability to acquire internal information from agricultural materials. This need is particularly relevant to controlled environment agriculture (CEA), where frequent nondestructive assessment of crop water status, stress responses, and disease development can support precise environmental regulation and crop management.

Terahertz (THz) waves generally refer to electromagnetic radiation in the frequency range of 0.1–10 THz, located between the microwave and infrared regions of the electromagnetic spectrum. With advances in femtosecond lasers, semiconductor THz sources, detectors, and artificially structured devices, THz technology has gradually expanded from fundamental physics research to material analysis [11], biological detection [12], food safety [13], and agricultural sensing [14] (Figure 1). Moisture, molecular composition, tissue structure, and dielectric properties of agricultural materials can all affect the amplitude, phase, absorption, and refraction of THz waves during propagation [15–17]. In particular, water exhibits pronounced dielectric loss in the THz frequency range, while various weak intermolecular interactions and low-frequency molecular vibrations also occur within this region. In addition, dielectric contrasts among different tissues and components can generate spatial variations in THz responses. These characteristics enable THz technology to acquire information on moisture status, chemical composition, and internal structure that cannot be fully captured by conventional surface optical techniques, thereby providing new dimensions of information for the nondestructive analysis of agricultural samples.

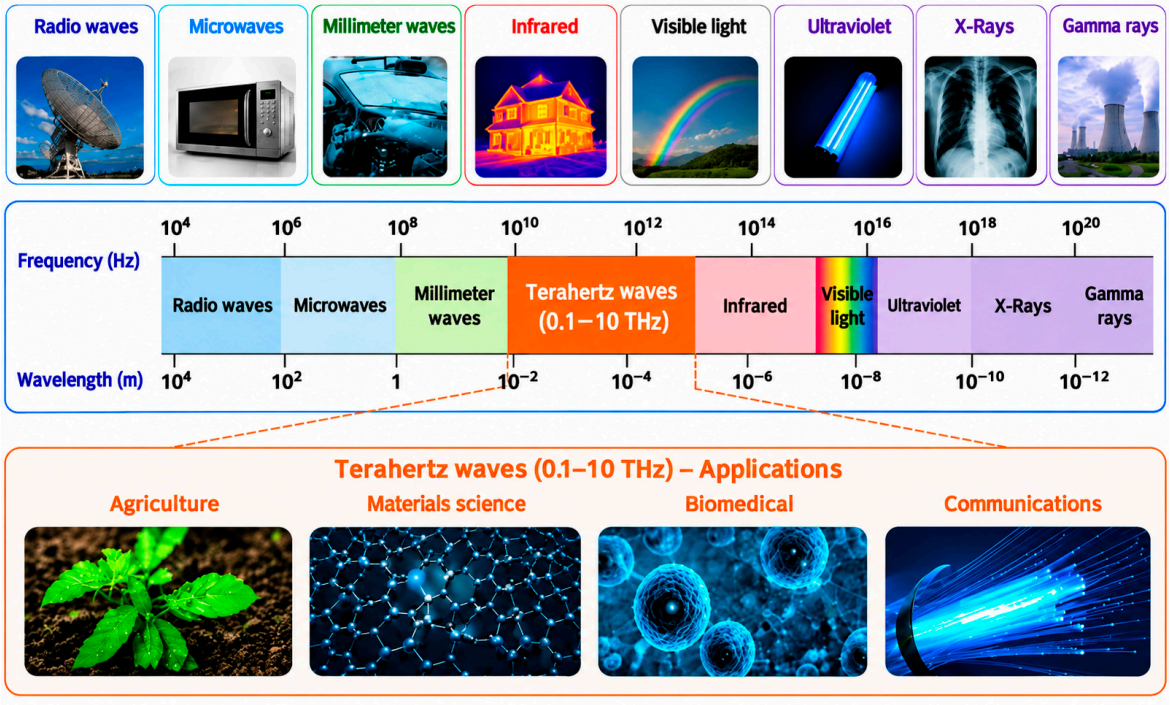



**Figure 1.** Position of terahertz waves in the electromagnetic spectrum and their major application fields.

In recent years, THz technology has been applied to seed quality and germplasm identification [18,19], soil property and contamination detection [20,21], crop physiological and stress monitoring [22,23], and agricultural product quality and safety assessment [24]. Meanwhile, technical approaches involving quantitative modeling, spatial imaging, and enhanced sensing have continued to diversify. The fundamental basis and applicable conditions of THz detection vary considerably among different agricultural materials and samples. Moisture content, sample thickness, tissue structure, and matrix composition may serve as useful sources of detection information, but can also induce strong absorption, scattering, and overlapping responses. Consequently, the focus of agricultural THz research has gradually shifted from simply demonstrating whether a specific object exhibits distinguishable responses toward defining the applicability ranges of different detection modes and evaluating signal stability and reliability under complex conditions.

As THz sensing increasingly generates multidimensional data in the time domain, frequency domain, and spatial imaging domain, data analysis methods have become increasingly important for improving detection performance. Machine learning methods, such as support vector machines and random forests, can address nonlinear relationships in agricultural THz data [25,26], while convolutional neural networks and other deep learning models further enhance automatic feature extraction from spectra and images [27–29]. In addition, the fusion of THz information with near-infrared spectroscopy, hyperspectral imaging, machine vision, and other sensing modalities provides new opportunities for jointly characterizing the internal state, chemical composition, and external phenotype of agricultural targets. However, most existing models have been developed using specific samples under controlled experimental conditions, with relatively limited datasets. Distribution shifts caused by differences in instrumental parameters, sample conditions, and environmental factors may therefore compromise model transferability and practical performance.

Although existing studies have demonstrated the potential of THz technology for nondestructive agricultural sensing, several challenges still hinder its large-scale application. Agricultural samples are generally characterized by high moisture content, heterogeneity, and complex multicomponent matrices. Water vapor absorption, tissue scattering, and matrix effects can weaken useful THz responses, while the sensitivity and selectivity of conventional THz detection for pesticides, pathogens, and other trace targets remain to be improved. Furthermore, current THz systems generally suffer from relatively high equipment costs, limited system integration, and insufficient adaptability to in situ monitoring scenarios, including greenhouses and other controlled production environments, while standardized protocols for data acquisition and model evaluation are still lacking [13,14,29]. Therefore, the development of agricultural THz technology requires not only improvements in detection accuracy under laboratory conditions, but also solutions for reliable signal acquisition in complex matrices, model generalization across objects and environments, and the miniaturization and online deployment of detection systems.

Although THz sensing has demonstrated considerable potential in agricultural engineering, its practical performance depends not only on the characteristics of agricultural materials but also on the sensing technologies employed. Different THz sensing approaches, including THz time-domain spectroscopy (THz-TDS), THz frequency-domain spectroscopy (THz-FDS), THz imaging, and resonance-enhanced sensing, differ in their information acquisition capabilities, detection sensitivity, and suitability for practical applications. Therefore, a systematic review of THz sensing technologies is necessary to clarify their underlying sensing mechanisms, technical characteristics, and applicability to different agricultural targets. Existing reviews have mainly focused on the fundamental principles of THz technology, agricultural product detection, or data analysis methods,

while systematic comparisons linking sensing technologies, material response mechanisms, agricultural applications, and practical limitations remain relatively limited. Accordingly, this review organizes agricultural THz sensing research according to the framework of "material response mechanisms–detection modes–intelligent data analysis–agricultural applications–engineering translation." First, the detection characteristics of THz time-domain spectroscopy (THz-TDS), THz frequency-domain spectroscopy (THz-FDS), and THz imaging, together with their major interaction mechanisms with agricultural materials, are introduced. Subsequently, chemometrics, machine learning, deep learning, and multimodal data fusion methods are reviewed. Application advances and key limitations are then summarized across the agricultural production chain, encompassing seeds, soil, crop growth, and agricultural product quality and safety. Finally, challenges associated with reliable detection of complex samples, model generalization, and equipment miniaturization are discussed to provide a reference for the further application of THz technology in intelligent sensing under practical agricultural conditions, with particular relevance to nondestructive crop monitoring in controlled environment agriculture.

ChatGPT (GPT-6, OpenAI) was used to assist in generating selected graphical elements for the conceptual illustrations presented in Figures 2, 4, and 5. These elements were subsequently edited, assembled, and refined by the authors using Adobe Photoshop. The spectral curves, PCA scatter plot, and heatmaps in Figure 4, and the resonance curves in Figure 5b, are schematic representations rather than results obtained from experimental measurements or numerical simulations. The numerical performance indicators in Figure 5 were taken from the cited published studies. All graphical content was reviewed by the authors for scientific accuracy, originality, and consistency with the cited literature.

## 2. Terahertz Sensing Technologies and Mechanisms in Agriculture

The development of THz technology has provided a nondestructive analytical approach based on electromagnetic response characteristics for acquiring agricultural information beyond conventional physicochemical measurements [30,31]. According to the mode of signal acquisition, current THz detection techniques mainly include terahertz time-domain spectroscopy (THz-TDS), terahertz frequency-domain spectroscopy (THz-FDS), and THz imaging based on these spectroscopic or frequency-domain measurements [32–34]. THz-TDS records the time-domain electric field and converts it into frequency-domain amplitude and phase information through Fourier transformation. Optical parameters such as the absorption coefficient and refractive index can then be further derived, making THz-TDS suitable for compositional analysis, state discrimination, and quantitative prediction of agricultural materials [29]. In contrast, THz-FDS directly acquires response characteristics at different frequencies through frequency scanning. Although it provides relatively limited time-domain information, it offers certain advantages for narrowband detection, system miniaturization, and rapid measurement. With the development of miniaturized THz sources, integrated detectors, and enhanced sensing structures, THz-FDS has shown increasing potential for portable and on-site detection [35,36]. THz imaging further incorporates spatial scanning or array-based detection into spectroscopic or frequency-domain measurements to obtain two-dimensional or even three-dimensional spatial distribution information, enabling the characterization of internal structures, localized anomalies, and spatial variations in agricultural materials [37]. Table 1 summarizes the information acquisition characteristics and suitable analytical targets of these three THz detection modes.

**Table 1.** Information Acquisition Characteristics and Applicable Targets of Three THz Detection Modalities.

| Detection Modality | Information Acquired | Suitable Analytical Targets |
| --- | --- | --- |
| THz-TDS | Time-domain waveform, amplitude, phase, absorption coefficient, refractive index | Compositional analysis, quantitative analysis |
| THz-FDS | Frequency-response characteristics | Rapid detection, portable sensing |
| THz Imaging | Spatial distribution, regional variations, internal structure | Defect analysis, state visualization |

The time-domain waveforms, frequency-domain amplitudes, phases, absorption coefficients, refractive indices, and spatial images obtained using different detection modes essentially originate from changes in the electromagnetic response generated by the interaction between THz waves and agricultural materials. Agricultural materials are typically characterized by high moisture content, multicomponent composition, and heterogeneity. Moisture, molecular composition, and tissue structure may simultaneously affect the absorption, phase delay, refraction, and scattering of THz waves during propagation. Therefore, THz techniques do not directly measure agricultural attributes such as seed vigor, plant stress, or agricultural product quality. Instead, they first acquire electromagnetic responses associated with the internal state of the material and subsequently establish relationships between these responses and target attributes through spectral analysis, imaging, and data-driven modeling [29,38]. From the perspective of information sources in agricultural materials, the major THz responses can be broadly categorized into three types: moisture-dominated responses, molecular vibrational responses, and tissue dielectric-contrast responses. In practical samples, these responses often coexist and are coupled with one another (Figure 2).

(1) **Moisture response.** Moisture is one of the most significant factors affecting the THz response of agricultural materials. Because water molecules possess a strong dipole moment and exhibit pronounced dielectric loss in the THz frequency range, variations in moisture status can substantially affect THz wave attenuation, phase, and dielectric response [39]. Seed imbibition and germination, plant dehydration and water stress, as well as the ripening and storage of agricultural products, are accompanied by varying degrees of moisture migration, allowing THz signals to indirectly characterize moisture content and its spatial distribution. It should be noted that moisture can serve as useful detection information but may also mask weaker compositional or structural responses because of its strong absorption. This represents an important limitation of THz detection for agricultural samples with high moisture content.

(2) **Molecular vibrational response.** The THz frequency range encompasses certain weak intermolecular interactions, hydrogen-bond vibrations, lattice vibrations, and low-frequency conformational motions of macromolecules. Differences in molecular structures and intermolecular interactions may therefore produce distinct absorption or resonant responses in the THz range [40]. This mechanism provides a theoretical basis for identifying pesticides, plant growth regulators, functional components, and certain contaminants [41–43]. For target substances with well-defined characteristic absorption peaks, THz spectroscopy can also be combined with computational methods such as density functional theory (DFT) to analyze the correspondence between characteristic peaks and molecular vibrational modes, thereby improving the physical interpretability of the detection results.

(3) **Tissue dielectric-contrast response.** Agricultural materials consist of moisture, cellular tissues, air voids, and various organic components, resulting in differences in complex

dielectric properties among different regions. When THz waves propagate through tissue interfaces, pores, or defective regions, their propagation velocity, attenuation, and scattering behavior may change, thereby producing distinguishable spatial response contrasts [44,45]. Tissue dielectric contrast therefore provides an important basis for using THz imaging to characterize internal seed structures, defects in nuts, tissue boundaries, and spatial heterogeneity. Unlike moisture and molecular responses, which are primarily reflected in overall spectral variations, this type of information places greater emphasis on spatial contrast among different regions.

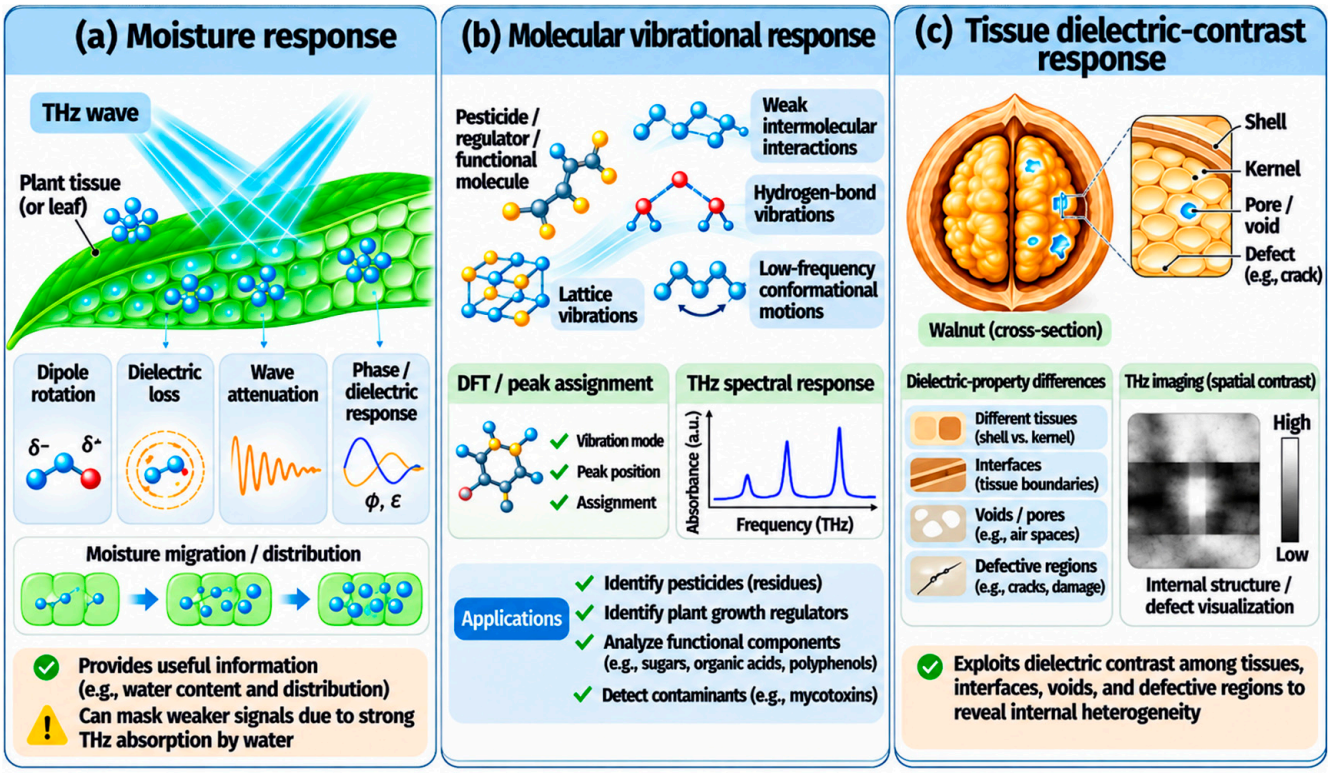



**Figure 2.** Schematic illustration of the major terahertz (THz) response mechanisms in agricultural materials: (**a**) moisture response; (**b**) molecular vibrational response; and (**c**) tissue dielectric-contrast response.

Overall, there is a clear correspondence between different THz information acquisition modes and the response mechanisms of agricultural materials. THz-TDS and THz-FDS primarily provide spectral information related to moisture, molecular composition, and dielectric properties, whereas THz imaging further incorporates the spatial dimension, enabling direct characterization of internal structures and regional variations. Together, these mechanisms determine the types of information that can be detected by THz technology in different agricultural applications and define its range of applicability, while providing a unified physical basis for subsequent data analysis and applications involving seeds, soil, crops, and agricultural product quality and safety.

## 3. Intelligent Analysis of Agricultural THz Data

THz spectroscopic and imaging data are characterized by high dimensionality, strong intervariable correlations, and substantial sample-to-sample variability. In agricultural samples, water, tissue structure, and target constituents may also produce coupled responses. Therefore, data analysis is a critical step in translating THz electromagnetic responses into meaningful agricultural attributes. Current THz studies in agriculture still predominantly

rely on conventional methods such as partial least squares (PLS) and support vector machines (SVMs), whereas the application of deep learning remains relatively limited, mainly due to constraints associated with the availability of independent samples and the cost of data annotation [46,47]. Therefore, algorithm selection should comprehensively consider the data modality, sample size, and detection task rather than simply pursuing greater model complexity.

### *3.1. THz Spectral and Image Analysis*

Agricultural THz data primarily consist of one-dimensional spectra and two- or three-dimensional imaging data. Although both originate from the same electromagnetic response processes, they differ in data structure and the information they contain. A single THz spectrum typically contains a large number of continuous frequency variables with strong correlations between adjacent frequency points, whereas the number of truly independent agricultural samples is often much smaller than the number of spectral variables. Under such high-dimensional, limited-sample conditions, methods such as principal component analysis (PCA), competitive adaptive reweighted sampling (CARS), and successive projections algorithm (SPA) can be used to reduce redundant variables or select informative frequency bands [48,49]. Partial least squares regression (PLSR) and support vector regression (SVR) are suitable for predicting continuous variables such as moisture, protein, and target constituent contents, whereas support vector machines (SVMs) and other classification models are commonly used to identify varieties, quality states, and contamination categories [46,50]. For example, Yang et al. combined THz spectroscopy with chemometric methods for corn variety discrimination and employed feature selection to reduce the influence of redundant variables on classification performance [50]. Therefore, conventional feature engineering and statistical learning methods remain highly applicable when sample sizes are limited.

When discriminative information is distributed across multiple frequency bands and exhibits complex nonlinear relationships, one-dimensional convolutional neural networks (1D-CNNs) can directly learn local spectral patterns along the frequency axis. For example, Pu et al. combined THz-TDS with a CNN to identify Citri Reticulatae Pericarpium from different geographical origins [51]. Chen et al. further employed THz spectroscopy and CNNs to classify different wheat varieties [52]. Such approaches reduce dependence on manually constructed features, but their advantages depend on whether the training samples adequately represent the underlying data distribution. For relatively small datasets in which class differences are mainly concentrated within a limited number of characteristic frequency bands, increasing network depth does not necessarily outperform conventional models such as SVM and PLS.

THz imaging contains spatial information such as textures, edges, and internal regions; therefore, CNNs and lightweight neural networks are more suitable for automatic feature extraction from such data. Shen et al. employed THz spectroscopic imaging combined with a CNN to identify impurities in wheat and achieved high classification performance [53]. Ge et al. further applied MobileViT-E to analyze THz images of sunflower seeds, reflecting a growing emphasis on balancing lightweight model design with computational efficiency [54]. Compared with one-dimensional spectra, the primary advantage of THz image-based models lies in their ability to exploit intrinsic spatial information.

It should be emphasized that the model architecture should correspond to the physical dimensionality of the data. Adjacent variables in a one-dimensional THz spectrum represent relationships between continuous frequencies, whereas adjacent pixels in a genuine THz image represent spatial neighborhoods. Although rearranging a one-dimensional spectrum into a two-dimensional matrix and subsequently applying a 2D-CNN may improve

classification performance on a specific dataset, the artificially constructed two-dimensional adjacency does not represent the actual spatial structure of the sample. Therefore, model evaluation should consider not only predictive accuracy but also whether the data representation preserves the original physical meaning of the THz signals. To further compare different THz data types, analytical tasks, and suitable models, Table 2 summarizes their data characteristics, commonly used analytical methods, applicable conditions, and major limitations.

**Table 2.** Comparison of Agricultural THz Data Characteristics, Analytical Tasks, and Applicable Models.

| THz Data and Task | Main Data Characteristics | Common Analytical Methods | Applicable Conditions | Major Limitations |
|---|---|---|---|---|
| Spectral quantitative prediction | Numerous continuous frequency variables with strong collinearity | PCA/CARS/SPA + PLSR/SVR | Continuous variables such as moisture, protein, and constituent concentrations; limited sample size | Susceptible to variations in sample thickness, moisture content, and batch |
| Spectral classification | High dimensionality, small sample size, and potential nonlinearity | SVM, RF, PLS-DA | Identification of variety, geographical origin, contamination, and quality grade | Parameter and feature selection affect model performance; cross-batch stability requires validation |
| Automated full-spectrum analysis | Combined contributions of weak responses across multiple frequency bands | 1D-CNN | Complex spectral patterns with relatively sufficient sample sizes | Large number of parameters and susceptibility to overfitting with small datasets |
| 2D THz imaging | Contains texture, edge, and spatial-region information | CNN, ResNet, MobileNet, MobileViT | Internal defects, impurities, seed quality, and region identification | Imaging speed and the availability of annotated data limit practical application |
| Image enhancement and reconstruction | High noise and limited resolution or sampling efficiency | CNN, GAN, super-resolution networks | Rapid imaging and recovery of weak structural features | Reconstructed results may introduce artificial features |
| Multi-source/ multimodal data | Differences in information dimensionality and underlying physical mechanisms | Feature-level fusion, joint learning, decision-level fusion | Ambiguous or insufficiently specific information from THz data alone | Data alignment, scale differences, and collinearity/confounding issues |

### *3.2. Model Development and Validation with Limited Samples*

Compared with large-scale public datasets such as those available for natural images, acquiring independent samples and reliable labels is relatively costly in agricultural THz research. Moreover, a single sample can often generate a large number of spectral variables, image pixels, or repeated measurements, resulting in a typical "high-dimensional data with limited independent samples" scenario. Conventional models such as SVM and PLS remain considerably more prevalent than deep learning methods in current studies [46], further reflecting the constraints imposed by dataset size on algorithm selection.

In studies with limited sample sizes, a clear distinction should be made between the number of observations and the number of independent samples. If different spectra, image

regions, or repeated measurements obtained from the same sample are randomly assigned to both the training and test sets, data leakage from the same source may occur, causing the model to learn sample-specific characteristics rather than the target attributes [55,56]. For example, Ge et al. [54] developed a MobileViT-E model using 2340 THz images of sunflower seeds and evaluated its performance using an 8:2 training–test split. Since THz imaging may generate multiple frequency-dependent images from the same specimen, such datasets require careful sample-level partitioning to ensure that correlated observations from an individual seed do not appear in both subsets. Therefore, training and test sets should, whenever possible, be partitioned at the level of independent biological samples.

To address insufficient training samples, data augmentation, generative models, and transfer learning have increasingly been applied to agricultural spectral analysis [57,58]. To overcome the limited availability of THz spectra for pesticide identification, Yang et al. combined a Wasserstein generative adversarial network (WGAN) with ResNet, using generated samples to expand the training dataset and facilitate deep feature learning. In this study, THz spectral responses were transformed into two-dimensional representations, and WGAN-generated samples were used to support ResNet training [59]. Such an approach requires strict separation of original training and test samples before data generation to prevent test-related information from entering the model development process. However, synthetic samples are still derived from the distribution of the original data and should therefore be used only for model training rather than as substitutes for real independent samples in performance validation. Similarly, when deep learning is applied to THz image reconstruction, it is essential to verify whether the enhanced images faithfully preserve the original THz responses.

In addition to increasing the amount of training data, reducing model complexity is another important strategy for adapting to small-sample agricultural THz datasets. Lightweight networks can reduce both the number of model parameters and computational requirements. The MobileViT-E model developed by Ge et al. and MobileNetV3-GS used for wheat germination detection exemplify this trend [54,60]. The influence of training sample size was also examined by Zhang et al. [61] in THz-based identification of bacterial blight-resistant rice seeds. Their results showed that CNN performance improved with increasing training data, whereas SVM exhibited comparatively stable performance with smaller training sets, illustrating the importance of considering sample size when selecting a classification algorithm. For spectral tasks with relatively simple class boundaries and only tens to hundreds of samples, SVM, PLS, and RF may still provide greater stability than deep networks with large numbers of parameters. In contrast, the advantages of automatic feature learning offered by CNNs become more evident when the data contain complex spatial structures or numerous local features. Therefore, there is no fixed performance hierarchy between conventional machine learning and deep learning; algorithm selection should be determined by sample size, data structure, and the specific detection objective.

Model evaluation strategies also directly affect the credibility of reported performance. Current agricultural THz studies commonly employ random train–test splits or cross-validation for model evaluation. Although these approaches can characterize predictive performance within the same data distribution, they do not adequately represent performance on new cultivars, new batches, or under different measurement conditions. For example, Hu et al. [62] evaluated rice seed vigor using 420 seeds from a single hybrid variety, while Lu et al. [63] investigated cold injury in one tea cultivar under controlled temperature conditions. Although these studies demonstrated predictive performance under their respective experimental settings, broader validation across cultivars and environmental conditions remains important. In agricultural product safety detection, Chen et al. [64] developed THz-FDS quantitative models mainly using pesticide mixtures in

glutinous rice flour, indicating the need for more systematic evaluation across different food matrices. By contrast, Yang et al. [65] evaluated a THz imaging-based framework across several seed types, providing a useful example of efforts to assess applicability beyond a single seed category. In particular, classification accuracies approaching 100% should be interpreted cautiously when obtained from small, single-source datasets, with careful consideration of the sample-partitioning strategy, number of repetitions, and independent test results [66,67]. Rather than pursuing marginal improvements of a few percentage points on the same dataset, clearly reporting the number of independent samples, preventing same-source data leakage, and providing performance on independent test sets are more informative for assessing the practical reliability of THz-based models.

### *3.3. Multimodal Fusion and Physics-Guided Interpretation*

Data-driven models can extract complex THz features, but they cannot generate specificity that is absent from the original signals. When water, tissue structure, and chemical constituents exert coupled effects on THz responses, high classification accuracy does not necessarily indicate that the model has identified the target factor itself [68,69]. Therefore, additional information dimensions should be introduced through multi-source sensing, while THz physical priors should be incorporated to constrain model interpretation.

In agricultural nondestructive testing, multi-source data fusion involving hyperspectral imaging, near-infrared (NIR) spectroscopy, and machine vision has been used to jointly characterize sample composition and phenotypic traits [70–74]. In THz research, Jiang et al. combined spectral and imaging features for maltose prediction in wheat, demonstrating the complementarity of spectral and spatial information within the same THz system [75]. Ge et al. further evaluated wheat quality using multi-source THz data and compared the effects of information fusion at different levels on classification performance [76]. Compared with THz information alone, cross-sensor multimodal fusion can introduce additional information based on different sensing mechanisms.

Multimodal fusion can generally be categorized into data-level, feature-level, and decision-level fusion, each offering distinct advantages in information preservation, feature complementarity, and model robustness [77–79]. For high-dimensional data such as THz and hyperspectral or NIR data, issues including data alignment, differences in scale, and redundant features must still be addressed during fusion. In recent years, cross-band sensing has also been introduced into agricultural product safety analysis. For example, Ma et al. developed a dual-modal SERS–THz sensor for the detection of multiple pesticides, increasing the information available for target identification through two distinct molecular response mechanisms [80]. However, the number of THz multimodal studies specifically developed for agricultural field applications and validated using independent samples remains limited. Therefore, the benefits of multimodal fusion should be assessed based on the incremental performance contributed by additional modalities relative to THz-only models, rather than solely on the high accuracy achieved after fusion.

In addition to expanding information sources, incorporating physical and chemical priors into models can improve the interpretability of THz data analysis. For target molecules with well-defined low-frequency vibrational characteristics, density functional theory (DFT) can be used to establish the correspondence between experimentally observed characteristic peaks and molecular vibrational modes [81]. Gao et al. further employed neural networks for the inverse design of metasurface sensors and combined THz-TDS with DFT to establish relationships between target-molecule responses and sensing structures [82]. Such approaches extend the role of algorithms from simply "assigning classes based on data" to "using target-response mechanisms to guide feature and sensing-structure design," provid-

ing an alternative strategy for detecting weak-response targets without merely increasing model complexity.

Overall, there is no universally optimal algorithm for agricultural THz data analysis; its suitability depends on the data structure, the number of independent samples, and the characteristics of the target information. Future research should shift from pursuing accuracy gains on individual datasets toward independent validation, complementary multi-source information, and reliable analysis constrained by underlying physical mechanisms.

## 4. Agricultural Applications of Terahertz Sensing

Based on the THz detection modes, material response mechanisms, and data analysis methods discussed above, THz technology has increasingly been applied to the acquisition of diverse types of information from agricultural samples in recent years. Owing to differences in composition, structure, physiological status, and detection requirements among agricultural materials and targets, current THz applications encompass multiple stages involving seeds, soil, crop growth, and agricultural product quality and safety, covering various scenarios throughout the agricultural production process. The following sections summarize recent advances in THz spectroscopy, imaging, and intelligent analysis methods for different agricultural targets according to the major sensing requirements in agriculture.

To examine the distribution of THz sensing research in agriculture, we searched the Web of Science Core Collection for records published between 1 January 2000 and 22 August 2026 using the following search query: TS = (terahertz OR THz) AND TS = (agricultur* OR crop* OR seed* OR soil* OR plant* OR leaf OR leaves OR grain* OR fruit* OR vegetable* OR food* OR pesticid* OR mycotoxin*) AND DOP = 2000-01-01/2026-08-22. The initial search retrieved 3277 records. After refining the search results by document type (Article), 2441 records remained. Original research articles investigating THz-based sensing of agricultural materials or relevant contaminants were considered eligible. The remaining records were screened according to the scope of this review, and 34 records were excluded because they were duplicates, were unrelated to agricultural applications, or did not report relevant THz sensing results. Consequently, 2407 studies were included in the final statistical analysis.

The included studies were analyzed according to their publication year, principal sensing modality, and primary agricultural application. Figure 3a presents the annual number of research articles published from 2000 to 2026. For Figure 3b, the studies were classified into three sensing modalities: THz time-domain spectroscopy, THz frequency-domain spectroscopy, and THz imaging. For Figure 3c, the studies were grouped into seven application categories: seed quality and germplasm identification, soil assessment and contaminant detection, crop water-status monitoring, crop stress and disease detection, agricultural product quality assessment, contaminant detection in agricultural products, and other applications. Studies involving multiple sensing modalities or application areas were assigned to a single category in each analysis according to their primary research objective. The percentage of each category was calculated by dividing the number of studies in that category by the total number of included studies and multiplying by 100. Each study was counted only once in each classification, and the resulting distributions are presented in Figure 3.

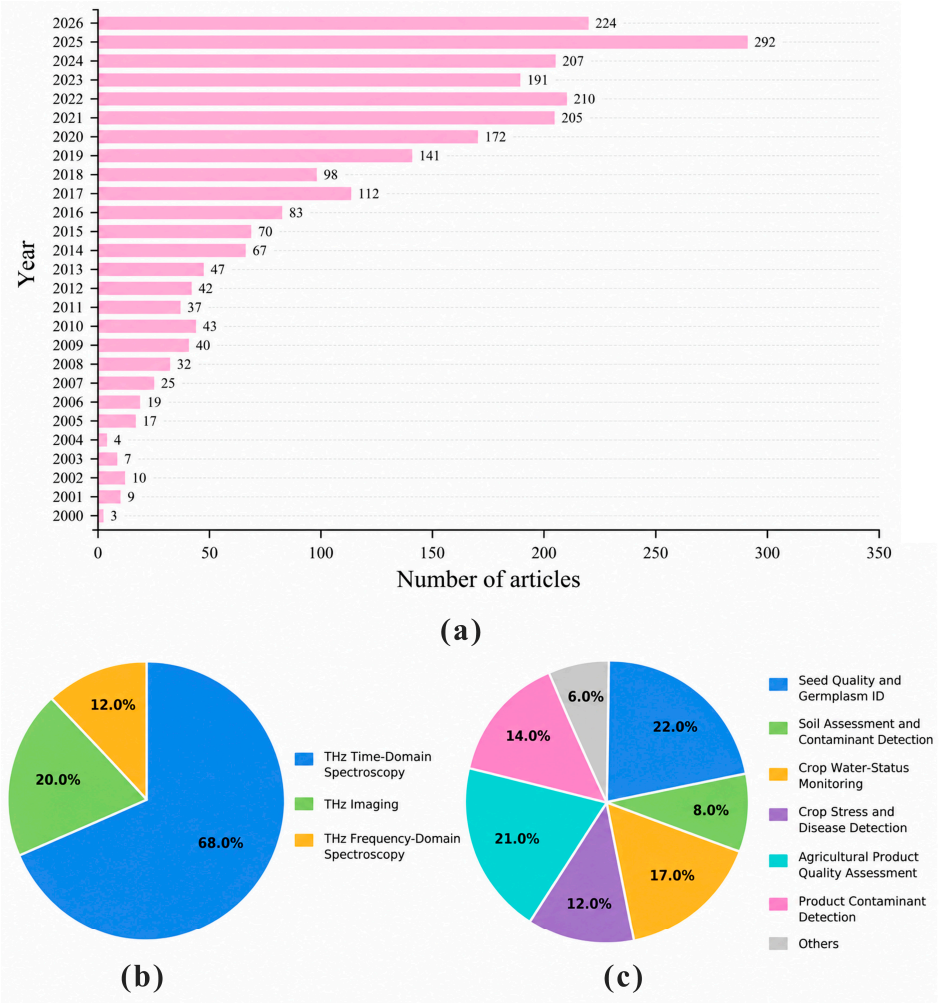



**Figure 3.** Publication trends and research distribution of terahertz (THz) sensing in agriculture. (**a**) Annual number of research articles indexed in the Web of Science Core Collection from 2000 to 2026; (**b**) distribution of studies by THz sensing modality; (**c**) distribution of studies across different agricultural application areas.

### *4.1. Seed Quality and Germplasm Screening*

Seed quality directly affects crop germination, stand establishment, and ultimately yield. Variations in internal constituents, including water, starch, proteins, and lipids, as well as structural differences in tissues such as the embryo and endosperm, can influence the absorption, phase, and dielectric responses of THz waves during propagation. THz spectroscopy and imaging can therefore characterize differences in seed composition and internal structure, providing nondestructive approaches for assessing seed vigor, varietal purity, stress resistance, and germplasm identity [32,83].

Seed vigor and internal quality assessment represent important applications of THz sensing. Gente et al. acquired the transmission responses of sugar beet seeds using THz-TDS and developed an automated classification approach based on differences in THz signals, enabling nondestructive discrimination between normal and defective seeds [84]. Subsequently, Hu et al. combined THz spectroscopy with chemometric methods to classify rice seeds with different vigor levels based on their spectral differences [62]. With the introduction of THz imaging and deep learning, spatial features have increasingly been incorporated into seed vigor assessment. Ge et al. combined THz imaging with a MobileNetV3-GS model to identify wheat seeds at different germination states, enabling rapid and nondestructive classification of germination status [60]. While spectroscopic

responses primarily reflect differences in overall seed composition and physiological state, THz imaging provides additional spatial information, offering complementary dimensions for evaluating seed vigor and internal quality.

For seed purity and authenticity assessment, compositional differences among varieties and adulterated samples provide a basis for THz discrimination. Yang et al. combined THz time-domain spectroscopy with an extreme learning machine (ELM), principal component regression (PCR), and partial least squares regression (PLSR) to develop models for assessing the purity of hybrid rice seeds, with ELM showing favorable stability and predictive performance [85]. To extract informative features from complex spectra, feature-selection methods such as Relief, random forest, and minimum redundancy maximum relevance (mRMR) have been used to identify highly discriminative frequency bands, followed by Hilbert transform-based analysis for detecting adulteration in rice seeds [86]. Spectral variations associated with varietal and adulteration differences thus provide an important basis for THz-based assessment of seed purity and authenticity.

Screening for stress and disease resistance represents another application of THz sensing in germplasm evaluation. Wang et al. used the time-domain and refractive-index spectra obtained by THz-TDS to nondestructively discriminate drought and cold resistance in forage seeds. They further developed a multilayer structural propagation (MSP) model based on effective-medium and wave-propagation theories to investigate the effects of constituents such as proteins and carbohydrates on THz propagation [87]. For screening rice germplasm for resistance to bacterial blight, Zhang et al. separately combined THz imaging and hyperspectral imaging with convolutional neural networks (CNNs) to nondestructively distinguish resistant from susceptible rice seeds [61]. Differences in internal composition and structure between stress- or disease-resistant and susceptible seeds can produce distinguishable THz responses, providing an additional source of information for rapid germplasm screening.

For the identification of genetically modified (GM) seeds, existing studies have primarily exploited subtle differences in THz responses among seeds with different genetic backgrounds for pattern recognition. Liu et al. combined THz spectroscopy with pattern-recognition methods to distinguish GM from non-GM soybean seeds and identified THz response differences that could be used for classification [88]. THz spectroscopic imaging combined with chemometric analysis has also been applied to the identification of GM rice seeds [89]. To address the relatively weak spectral differences among GM cottonseed samples, adaptive local iterative filtering (ALIF) and wavelet transform (WT) have been employed for signal denoising and feature enhancement, followed by discriminant analysis to classify four types of GM cottonseeds, achieving an accuracy of 98.33% [90]. For germplasm identification tasks involving subtle THz response differences, signal denoising, feature enhancement, and pattern recognition are therefore important data-processing steps for improving class separability. Representative applications of THz technology in seed vigor assessment, stress-resistance screening, and genetically modified seed identification are shown in Figure 4.

Representative studies in Table 3 illustrate the progression from spectral discrimination to spatial analysis and efficient THz imaging. Hu et al. [91] achieved 98.33% prediction accuracy for rice seed fullness using UVE–SPA–KNN, reducing spectral data by 97.5%. Subsequently, Wu et al. [92] evaluated 120 watermelon seeds from three cultivars, achieving 96.69% pixel accuracy with DeepLab V3+ for tissue segmentation. More recently, Yang et al. [65] reduced the imaging measurement ratio to 12.5%, with fullness errors below 5.56% across different seed types, while Li et al. [93] reported an average verification-set error of 3.37% for pumpkin seed fullness. However, differences in detection tasks and evaluation metrics limit direct comparisons of their reported performance.

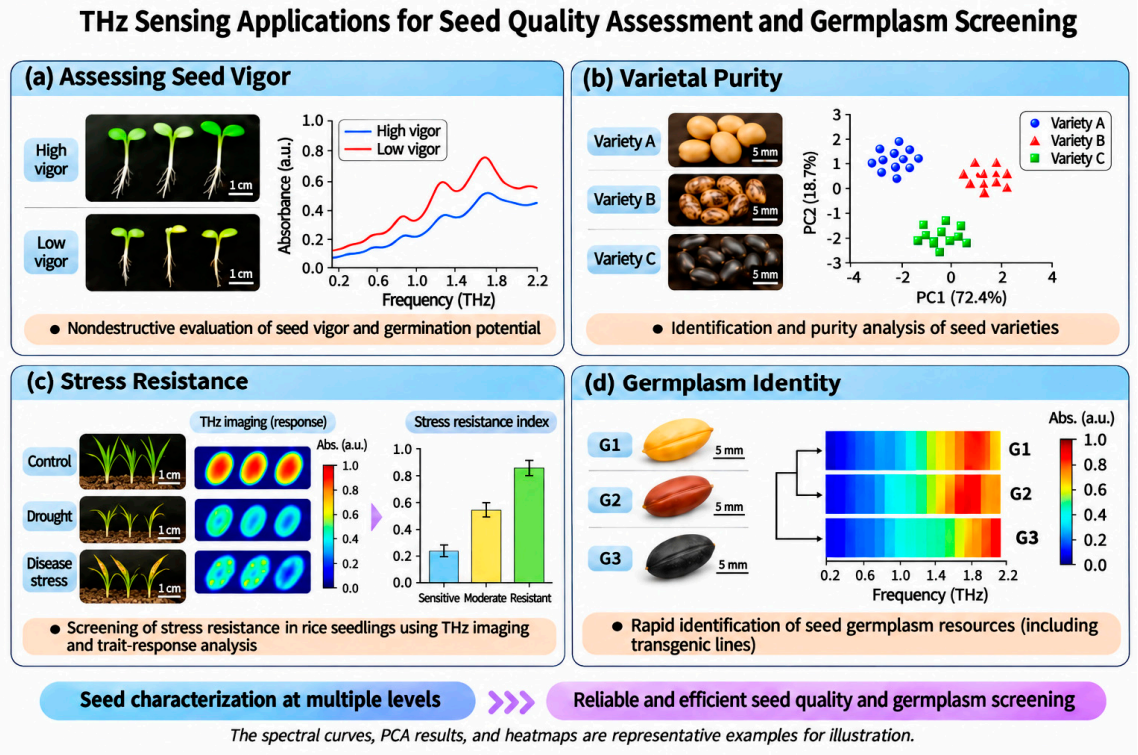



**Figure 4.** Schematic illustration of terahertz sensing applications in seed quality assessment and germplasm screening.

For seed detection, the key issue is no longer simply whether different categories can be distinguished, but whether the identified response features remain robust under more complex sample conditions. Similar concerns regarding sample variability and model generalization have also been recognized in nondestructive seed assessment using hyperspectral imaging and machine vision [94,95]. Variations in seed variety, geographical origin, moisture content, and individual structure may all affect THz responses, whereas most existing models have been developed using limited sample sets under controlled experimental conditions. Therefore, validation across varieties and sample batches will be essential for evaluating the practical applicability of THz-based seed detection.

**Table 3.** Advances in THz-Based Seed Quality Detection.

| Detection Target | Detection Purpose | Frequency Range (THz) | THz Technique | Data Analysis Method | Main Findings | Reference |
|---|---|---|---|---|---|---|
| Cotton seeds | GM identification | 0.1–3 | THz-TDS | Refractive index/absorption coefficient analysis | Distinguishable THz spectral responses were observed between GM and non-GM cottonseeds, providing a basis for their nondestructive identification | [96] |
| Maize seeds | Vigor assessment | 0.2–2.0 | THz-TDS | Two-dimensional correlation spectroscopy + SVM | Differences in THz responses between the endosperm and embryo regions enabled rapid classification of seeds with different vigor levels | [97] |

**Table 3.** *Cont.*

| Detection Target | Detection Purpose | Frequency Range (THz) | THz Technique | Data Analysis Method | Main Findings | Reference |
|---|---|---|---|---|---|---|
| Maize seeds | Moisture content determination | 0.1–2.5 | THz-ATR | iPLS, biPLS, siPLS + SVR | Moisture-sensitive spectral regions were selected to develop a high-accuracy model for moisture content prediction | [98] |
| Rice seeds | Seed fullness assessment | 0.1–3 | THz imaging | CARS, UVE, SPA + KNN | Empty and filled seeds were successfully distinguished, with the UVE-SPA-KNN model achieving an accuracy of 98.33% | [91] |
| Maize seeds | Spatial distribution of starch | 0.2–2.5 | THz imaging | Spectral–image fusion analysis | The spatial distribution of starch within seeds was visualized, extending the capability of THz-based compositional analysis | [99] |
| Watermelon seeds | Internal quality detection | 0.1–3 | THz imaging | Image smoothing and enhancement algorithms | THz image quality was improved, enabling the detection of internal structures in thin-shelled seeds | [100] |
| Watermelon seeds | Seed coat/kernel structure identification | 0.1–3 | THz imaging | SegNet, DeepLab V3+ | Deep learning enabled automated segmentation of seed tissues, achieving a pixel accuracy of 96.69% | [92] |
| Pumpkin seeds | Overall quality assessment | 0.1–3 | THz-TDS | CNN | A THz-CNN model was developed to distinguish seeds with different quality states | [101] |
| Multiple seed species | Internal quality detection | 0.1–3 | THz imaging | Compressed sensing + improved Real-ESRGAN | Image reconstruction quality was improved while reducing the number of samples required, facilitating rapid internal detection | [65] |
| Pumpkin seeds | Seed fullness assessment | 0.1–3 | THz imaging | Compressed sensing + super-resolution reconstruction | Imaging time was reduced and spatial resolution improved, enabling rapid seed quality assessment | [93] |

### *4.2. Soil Characterization and Contaminant Detection*

Soil moisture, composition, and contamination status directly affect crop root growth, water and nutrient utilization, and agroecosystem safety [102]. Variations in soil moisture, particle composition, and contaminant type can alter the absorption, scattering, and dielectric responses of THz waves during propagation. Consequently, THz spectroscopy has increasingly been applied to the nondestructive detection of basic soil properties and contaminants.

The characterization of basic soil properties and moisture is an important aspect of THz-based soil research. Dworak et al. distinguished different soil types by analyzing their THz absorption characteristics and demonstrated the potential of THz technology

for characterizing soil parameters such as moisture and organic matter [103]. In a subsequent study, Dworak et al. developed a THz hyperspectral imaging system operating at 250–370 GHz and demonstrated its ability to characterize differences in soil samples and particle-size-dependent scattering, highlighting the potential of spatially resolved THz measurements for soil analysis [104]. However, the THz response of soil is not determined solely by moisture content; particle composition and structure also affect signal propagation. Lee et al. investigated the combined effects of moisture content and particle size on THz signal attenuation. They found that increasing moisture content substantially enhanced THz attenuation, whereas variations in particle size altered the scattering characteristics [105]. These findings indicate that matrix effects, particularly water absorption and particle scattering, should be considered simultaneously when soil properties are inferred from THz measurements.

For the detection of heavy-metal contamination in soil, THz responses can be used to characterize different contamination states and associated changes in dielectric properties. Li et al. employed THz-TDS to analyze the absorption characteristics of soils contaminated with different chemical forms of lead and revealed a relationship between the speciation of heavy metals and their THz responses [106]. To investigate metal-ion adsorption, Cheng et al. used THz-TDS to monitor changes in chromium ions in bentonite and established a relationship between THz signals and metal-ion concentrations [20]. For the discrimination of multiple heavy-metal contaminants, THz spectroscopy combined with deep learning has also been applied to the classification and concentration prediction of soil samples contaminated with Cd, Ni, and Zn [107]. Existing studies have therefore addressed several tasks, including heavy-metal speciation analysis, concentration characterization, and multi-contaminant classification, demonstrating the potential of THz technology for screening heavy-metal contamination in soils.

Emerging contaminants, such as microplastics, have also become a focus of THz-based soil detection. Differences in the dielectric properties and THz spectral responses of polymers provide a basis for identifying microplastic types and estimating their concentrations. Nie et al. combined THz spectroscopy with machine learning and extracted characteristic spectral information from microplastic-contaminated soils to identify microplastics such as low-density polyethylene (LDPE) and polyvinyl chloride (PVC) [21,108]. Similar to heavy-metal detection, background responses arising from soil particles, moisture, and other constituents may overlap with the spectral features of microplastics. Therefore, the robust extraction of contaminant-specific features under complex matrix conditions remains an important consideration for practical applications.

The major challenge in THz-based soil detection lies in the coupled effects of water absorption, particle scattering, and multicomponent background interference under complex soil conditions. Future research should therefore focus on developing robust calibration models adaptable to different soil types and moisture conditions and strengthening systematic validation using real field soil samples.

### *4.3. Monitoring Crop Water Status*

Water status directly affects crop photosynthesis, stomatal regulation, and biomass accumulation, and is also an important physiological indicator for assessing drought stress and guiding precision irrigation [109–111]. Because water strongly absorbs THz radiation, changes in leaf water status can significantly alter the amplitude, phase, and dielectric response of THz signals. Therefore, plant water status represents one of the earliest and most representative applications of THz technology in crop physiological monitoring.

Early studies primarily focused on the response of THz signals to changes in plant water status. Hadjiloucas et al. were among the first to investigate changes in leaf water content

using THz transmission measurements. By establishing the relationship between transmitted THz signals and leaf water status, they demonstrated the feasibility of nondestructive monitoring of leaf water content [22]. Subsequently, the mathematical relationships between THz spectral parameters and leaf water content were further investigated to explore the extraction of water-related characteristic parameters [112]. These studies confirmed the sensitivity of THz waves to variations in leaf water status and laid the foundation for subsequent quantitative analyses based on absorption and dielectric responses. However, these early studies were mainly conducted on detached leaves under controlled conditions.

Building on the established relationship between THz responses and plant water status, subsequent studies further focused on quantitative water analysis and dynamic in vivo monitoring. Gente et al. combined THz-TDS transmission spectroscopy with an effective-medium model to simulate the contributions of water, air, and dry tissue to the dielectric response of leaves, enabling the nondestructive prediction of leaf volumetric water content. The predicted results showed good agreement with those obtained using the conventional gravimetric method [113]. Furthermore, Castro-Camus et al. performed continuous in situ THz-TDS measurements on intact Arabidopsis thaliana plants and characterized dynamic changes in leaf water status under drought treatment, diurnal variation, and abscisic acid (ABA)-induced conditions [114]. The extension from detached leaves to intact plants provided an experimental basis for the continuous monitoring of dynamic changes in plant water status using THz technology. However, these in vivo measurements were conducted under controlled conditions rather than in agricultural production environments.

Beyond bulk water status, THz imaging has further expanded the capability to characterize the spatial heterogeneity of water distribution in plant tissues. Zuo et al. investigated differences in THz responses among different regions of leaves and found that tissues such as veins and mesophyll exhibited distinct responses because of differences in water content and structural characteristics, providing a basis for analyzing the spatial distribution of leaf water [23]. Song et al. further employed THz-TDS imaging to investigate the spatiotemporal variations in water status in holly, ginkgo, and bamboo leaves. By reconstructing THz transmission-amplitude images, they visualized leaf water distribution and observed spatially heterogeneous water-loss patterns among different leaf regions during natural drying [37]. THz imaging therefore complements point-based spectroscopic measurements by providing spatial information, enabling further characterization of water distribution and dynamic water migration within leaves.

Collectively, these studies demonstrate that THz signals are highly sensitive to leaf water status and its spatiotemporal distribution. However, the major obstacle to practical application is no longer whether water content in an individual leaf can be detected, but rather how the measurement scale can be extended [115,116]. Laboratory measurements of individual leaves are well controlled, whereas canopy measurements are affected by leaf thickness, orientation, overlap, and ambient humidity, which alter THz propagation and signal intensity. Extending THz water monitoring to robust in situ canopy sensing therefore remains a critical scale-related challenge.

### *4.4. Crop Stress and Disease Assessment*

During crop growth, plants are exposed to both biotic stresses, such as pathogen infection, and abiotic stresses, including low temperature, abnormal light conditions, and nutrient deficiency [117–119]. Although these stresses arise from different causes, they can all induce changes in tissue water status, cellular structure, and physiological metabolism, thereby altering the dielectric properties and THz responses of plant tissues [120].

For biotic stress, early studies primarily focused on pathogen identification based on differences in their intrinsic THz responses. Li et al. employed THz spectroscopy and

imaging to analyze three pathogenic fungi associated with pear ring rot, cucumber powdery mildew, and grape gray mold. Their absorption and refractive characteristics over the 0.1–2.0 THz range were compared, and K-nearest neighbors (KNN), support vector machine (SVM), and backpropagation neural network (BPNN) models were used for identification. Among them, the SVM model based on characteristic images at 1.376 THz achieved an F1-score of 93.82% [121]. These results indicate that differences in dielectric and absorption responses among pathogen samples can provide discriminative information for classification.

In addition to directly identifying pathogens, research has gradually shifted toward detecting plant tissue responses following pathogen infection. Wang et al. combined THz-TDS with an enhanced attenuated total reflection (ATR) structure to improve the detection sensitivity for fresh leaves. By capturing changes in the electromagnetic response of tissues induced by pathogen infection, they achieved nondestructive monitoring of plant health status and early changes associated with fungal infection [122]. Zhou et al. further combined THz spectroscopy with imaging for the detection of apple Valsa canker, identifying diseased regions based on differences in THz responses between healthy and infected tissues [123]. Compared with direct pathogen identification, these approaches use the electromagnetic responses and spatial variations of infected tissues as detection features, thereby broadening the information available for THz-based disease detection.

With the development of highly sensitive THz sensing structures, increasing attention has been directed toward the direct detection of pathogens at low concentrations. To address the need for early detection of Fusarium head blight in wheat, Wang et al. developed a THz metamaterial sensor for pathogenic spores. By enhancing the interaction between pathogenic spores and THz waves through localized electromagnetic fields, the sensor enabled label-free quantitative detection of Fusarium spores, with a limit of detection of 10 spores/μL [124]. Compared with indirect identification based on responses of diseased tissues, this approach shifts the detection target upstream to pathogenic spores, providing a new technical route for early disease warning.

Beyond biotic stress, THz technology has also been extended to the monitoring of abiotic stresses such as temperature and light stress. Lu et al. employed THz spectroscopy to assess the degree of low-temperature injury in tea plants, identified distinct spectral responses among samples with different levels of freezing injury, and developed a model for predicting stress severity [63]. Gao et al. employed a multi-resonance THz metamaterial sensor to diagnose low-light stress in lettuce, using localized electromagnetic-field enhancement to improve sensitivity to physiological changes associated with low-light conditions [125]. Studies on low-temperature and low-light stresses further demonstrate that THz responses can be used to characterize environmentally induced physiological changes in plants, providing an additional approach for abiotic stress assessment.

Compared with the stress types described above, studies directly applying THz technology to the evaluation of plant nutritional status remain relatively limited. Existing research has mainly focused on characterizing the THz responses of physiological components such as chlorophyll. Coquillat et al. used THz-TDS to investigate the low-frequency vibrational characteristics of chlorophyll and its derivatives, showing that different chlorophyll-related components exhibit distinct THz responses [126]. Complementary sensing studies have also used multispectral imaging and electrochemical approaches to characterize chlorophyll-related traits and plant hormone status [127,128]. These findings provide a basis for using THz information to characterize plant physiological status. Nevertheless, compared with disease and water-stress detection, evidence supporting the direct use of THz technology to detect nutrients such as nitrogen, phosphorus, and potassium or to assess overall plant nutritional status remains limited. Both biotic and abiotic stresses can induce changes in

plant water status, tissue structure, and metabolism; therefore, variations in THz signals are not inherently stress-specific. Future research should focus on disentangling THz responses under multiple concurrent stresses and extracting stress-specific features.

### *4.5. Agricultural Product Quality Assessment*

Agricultural product quality encompasses multiple attributes, including moisture content, sugar content, functional components, internal structure, defects, and freshness. In this section, quality assessment primarily concerns the intrinsic physicochemical properties, structural integrity, and overall quality status of agricultural products, rather than the identification of hazardous contaminants. Conventional physicochemical methods generally require sampling and sample pretreatment, whereas conventional optical techniques have limited capability to acquire internal information from certain agricultural products [129,130]. Conventional optical techniques have also been widely applied for nondestructive evaluation of fruit quality and freshness [131–133]. THz waves are sensitive to variations in moisture, dielectric properties, molecular composition, and internal structure, enabling quality-related information to be acquired from both spectral and spatial dimensions. Current studies have mainly focused on three aspects: physicochemical quality parameters, internal structures and defects, and comprehensive quality status assessment [134].

For the detection of physicochemical quality parameters, existing studies have primarily exploited differences in THz absorption, dielectric, and resonance responses induced by variations in quality-related components. Moisture content is one of the most representative parameters. Time-domain, frequency-domain, and time–frequency features obtained over 0.75–1.1 THz, combined with models such as support vector machines (SVMs) and K-nearest neighbors (KNNs), have been used to distinguish apple and mango slices with different moisture levels [135]. Beyond moisture, THz spectroscopy combined with partial least squares regression (PLSR) has also been applied to the qualitative and quantitative analysis of hesperidin and naringin in citrus fruits [136]. To address the difficulty of acquiring internal quality information from fruits with thick peels, Karmakar et al. developed a printable sub-THz metamaterial sensing sticker, termed Meta-Sticker. Different resonance modes were used to characterize changes in the peel and internal tissues, enabling nondestructive evaluation of sugar content and dry matter content during the ripening of persimmon, pear, and mango fruits [24]. Thus, the quality attributes investigated using THz technology are no longer limited to moisture but also include functional components, sugar content, and dry matter. Because different attributes exhibit varying response intensities and detection depths, the detection modality should be selected according to the specific quality information of interest. Other sensing modalities have similarly been used to evaluate functional components and maturity-related attributes in agricultural products [137,138].

Unlike the physicochemical parameters described above, which are primarily characterized through spectral responses, the evaluation of internal structures and defects relies more strongly on the spatial information provided by THz imaging. For certain low-moisture nuts and grains, relatively low THz absorption losses facilitate penetration through the shell or outer layer to obtain information on internal structures. Reflection-mode THz imaging has been applied to detect internal decay in hazelnuts, enabling discrimination between healthy and decayed samples [139]. For walnut inspection, THz spectroscopy combined with SVM, random forest (RF), and KNN has been used for mold detection, while image segmentation has further enabled evaluation of kernel fullness [140]. Beyond two-dimensional imaging, advanced data analysis methods have expanded the utilization of internal structural information. Ge et al. [54] classified 2340 THz images of sunflower seeds using MobileViT-E, achieving 96.30% accuracy with an 8:2 training–test split. In comparison,

Lei et al. [141] employed three-dimensional THz computed tomography to quantify internal seed structures, reporting a correlation of R = 0.89 between kernel voxel intensity and kernel weight at 1.2 THz. These studies demonstrate complementary capabilities: two-dimensional imaging supports automated category recognition, whereas THz-CT enables quantitative internal assessment but requires more complex data acquisition. THz-based internal quality assessment has therefore evolved from spectral difference analysis to two-dimensional defect imaging and three-dimensional structural reconstruction, providing internal spatial information at different levels.

In addition to individual physicochemical parameters and structural characteristics, THz information can also be used for comprehensive quality status and category discrimination based on overall sample responses. During storage, agricultural products often undergo simultaneous changes in moisture distribution, tissue structure, and physicochemical properties, which collectively alter their THz responses. Geng et al. acquired spectral information from different edible oils using THz-TDS and combined it with pattern recognition methods to achieve rapid, non-contact classification of edible oils, extending the application of THz technology to comprehensive quality identification of liquid foods [142,143]. Rather than directly predicting a specific quality parameter, such studies focus on using THz information to characterize the overall status resulting from multiple concurrent quality changes, providing an alternative approach for evaluating the storage quality of agricultural products [144].

The water status and tissue structure of agricultural products determine the type of information accessible by THz techniques and the appropriate detection modality. Low-moisture nuts and grains are more suitable for internal structural imaging, whereas strong water absorption in fresh fruits and vegetables may obscure weaker responses from other constituents. Therefore, spectroscopy, imaging, or enhanced sensing approaches should be selected according to sample characteristics and target attributes, with particular emphasis on validating detection robustness under complex sample conditions.

### *4.6. Contaminant Detection in Agricultural Products*

Contaminant detection in agricultural products primarily involves the identification and quantification of hazardous substances, including pesticide residues, heavy metals, and mycotoxins. These contaminants may be introduced or accumulate during cultivation, processing, storage, and transportation, highlighting the need for rapid and minimally destructive detection methods [145,146]. Differences in the molecular structures and concentrations of contaminants, as well as their interactions with food matrices, enable THz detection to identify contaminants through characteristic spectral responses while also allowing weak-signal sensitivity to be enhanced using structures such as metamaterials, near-field enhancement devices, and microfluidic systems. Current research has mainly focused on pesticide residues, heavy-metal contamination, and mycotoxin detection [13,147]. Complementary food-safety sensing strategies, including MOF- and SERS-based platforms, have also been widely explored for contaminant detection [148–151]. Fluorescent, electrochemical, colorimetric, and microfluidic methods have further been applied to the detection of antibiotics, ethyl carbamate, molds, and foodborne pathogens [152–156].

Pesticide residues are among the most extensively investigated targets in THz-based agricultural product safety detection. Conventional THz spectroscopy primarily enables qualitative identification and quantitative analysis by exploiting differences in characteristic absorption and dielectric responses of pesticide molecules. Qin et al. employed THz-TDS to detect carbendazim mixtures through paper packaging and successfully obtained effective THz responses from the packaged samples [157]. In food matrices, THz frequency-domain spectroscopy (THz-FDS) combined with chemometric methods has also been applied

to pesticide identification and concentration prediction [64]. These studies demonstrate the feasibility of THz spectroscopy for pesticide detection. However, in real agricultural products, the weak responses generated by low-concentration analytes can be readily obscured by water absorption and complex matrix backgrounds, limiting the capability of conventional spectroscopic methods for direct detection of trace pesticide residues.

To enhance weak THz responses from trace pesticide residues, different sensing structures have been investigated with distinct advantages and validation levels. Ye et al. [158] found that field enhancement mainly influenced sensitivity at higher concentrations, whereas resonance matching with molecular fingerprint peaks was more critical at lower concentrations. Lee et al. [159] employed nanoslot antennas to achieve ppb-level detection and demonstrated pesticide residue imaging on an intact apple. In comparison, Ahmed et al. [160] numerically reported a refractive-index sensitivity of 208 GHz/RIU for a metamaterial sensor, whereas Zhang et al. [161] experimentally achieved a detection limit of 100 pg/mL for metaldehyde solutions using graphene-integrated metamaterials. Representative enhanced sensing structures are illustrated in Figure 5. For quantitative detection in food matrices, Tong et al. [162] integrated metal gratings with microfluidics, achieving approximately eightfold higher sensitivity than conventional THz transmission and a relative error below 5.3% in orange juice. Although tested with real orange-juice samples, this approach was evaluated under laboratory conditions rather than on a production line. Compared with approaches that primarily pursue high sensitivity using standard samples, this strategy integrates signal enhancement with sample handling, reflecting the growing demand for extending THz pesticide detection to complex matrices. These findings demonstrate different advances in sensitivity and practical applicability, although simulated and experimentally measured performance cannot be directly compared.

In addition to hardware-based signal enhancement, data-driven methods are mainly used to improve the interpretation of complex THz signals and the design of sensing structures. To address the limited stability of pesticide spectral recognition under small-sample conditions, the combination of a Wasserstein generative adversarial network (WGAN) and ResNet can improve pesticide recognition performance through data generation and deep feature extraction [59]. The role of artificial intelligence has also extended to THz sensor design. Gao et al. developed an inverse-design approach for metasurface sensors using SC_ISSA-BPNN and combined THz-TDS with density functional theory (DFT) to analyze the THz responses of target molecules, enabling targeted sensing-structure design for plant-related molecules such as abscisic acid, gibberellin, and folpet [82]. Data-driven approaches are therefore being applied not only to the classification of detection data but also to optimizing the matching between sensing structures and target-molecule responses.

In addition to pesticide residues, THz technology has also been investigated for screening agricultural products contaminated with heavy metals. Unlike organic pesticides with characteristic molecular vibrational responses, heavy-metal-related detection relies more strongly on changes in dielectric properties and overall THz responses induced by contamination. Metal-grating-enhanced THz sensing structures have been applied to detect copper sulfate contamination in fruit samples [163]. For the identification of multiple heavy-metal contaminants, THz time-domain spectroscopy combined with wavelet denoising and deep support vector machine models has been used to classify wheat samples contaminated with arsenic, lead, mercury, chromium, and cadmium, extracting discriminative features associated with different contamination states from complex spectra [26]. However, these methods mainly rely on indirect discrimination based on differences in the overall responses of contaminated samples, and their adaptability to different heavy-metal species, concentrations, and food matrices requires further validation.

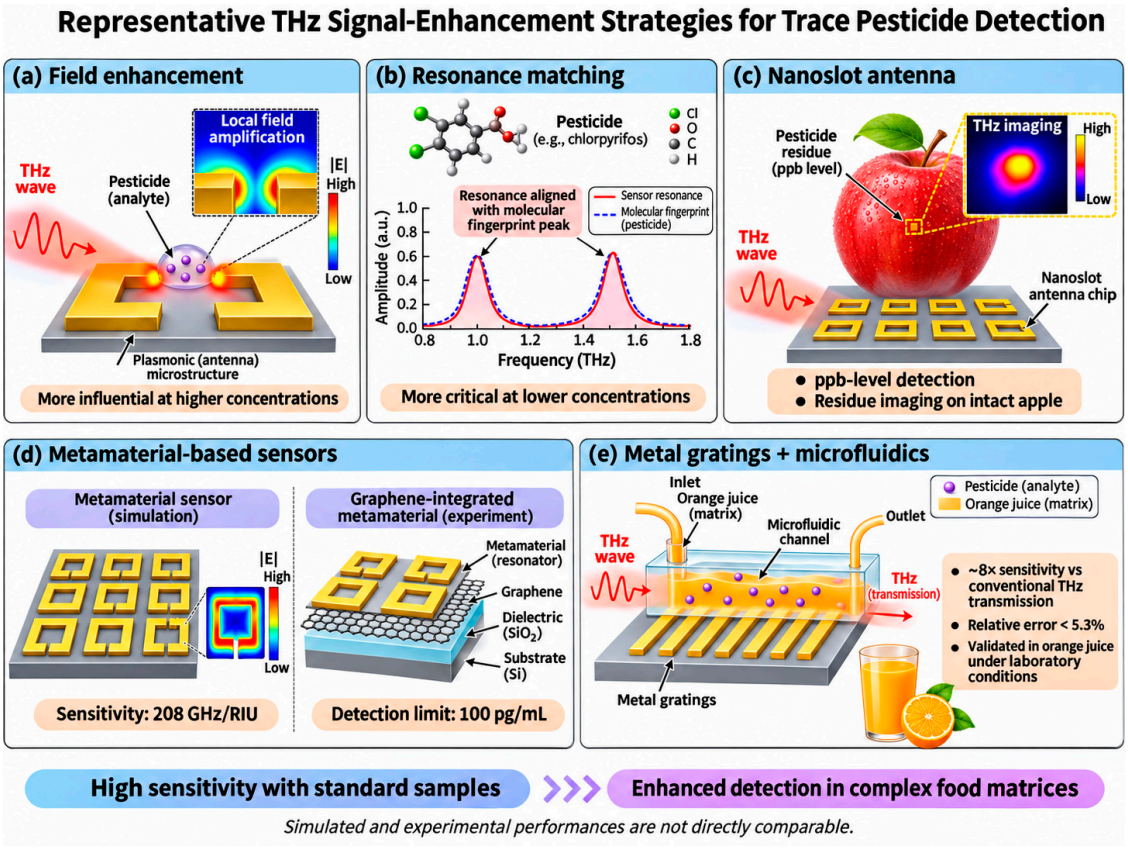



**Figure 5.** Schematic illustration of representative terahertz (THz) signal-enhancement strategies for trace pesticide detection: (**a**) local electromagnetic field enhancement; (**b**) resonance matching with molecular fingerprint absorption features; (**c**) nanoslot antenna-based sensing; (**d**) metamaterial-based sensing, including graphene-integrated metamaterials; and (**e**) metal grating-assisted microfluidic sensing for pesticide detection in complex food matrices.

Mycotoxin detection places greater emphasis on the capability of enhanced THz sensing to detect trace-level analytes. Because low concentrations of aflatoxins produce weak responses in conventional THz measurements, metamaterial resonant structures have been employed to amplify analyte-induced dielectric changes. Gold split-ring resonator metamaterials combined with THz-TDS have enabled label-free quantitative detection of AFB1 and AFB2 [164]. Building on this approach, bound-state-in-the-continuum (BIC) metamaterials exploit high-quality-factor resonances to enhance weak dielectric perturbations and, when combined with particle swarm optimization–support vector machine (PSO-SVM), enable the classification of multiple aflatoxins [165]. In such trace-detection tasks, metamaterials enhance weak dielectric perturbations, whereas pattern-recognition methods further exploit multidimensional resonance features, providing clear functional complementarity between sensing enhancement and data analysis.

The key challenge in THz-based agricultural product safety detection is not merely to improve classification accuracy, but to ensure selectivity and quantitative reliability under real-matrix and low-concentration conditions. Future studies should place greater emphasis on reporting limits of detection, recoveries, and repeatability in real samples and on validating THz detection performance using samples from different batches and established reference analytical methods.

Taken together, the above studies demonstrate that the basis of THz detection and the associated technical bottlenecks vary considerably across agricultural applications. Seeds and certain low-moisture agricultural products exhibit relatively low THz propagation losses, making them more suitable for acquiring information on internal composition and

structure. Plant water monitoring has a relatively well-established response mechanism associated with water absorption; however, environmental and structural factors in complex crop canopies can still compromise measurement stability. In soils, the coupled effects of water absorption, particle scattering, and multicomponent responses make complex matrix interference a major obstacle to quantitative detection. For crop stress and disease detection, a key challenge is to distinguish overlapping THz responses arising from stress-induced changes in water status, tissue structure, and metabolism. In contrast, agricultural product safety detection places greater emphasis on low-concentration target analytes, with research increasingly shifting toward enhanced sensing strategies and validation in real sample matrices. Therefore, the focus of THz research across different agricultural scenarios has gradually progressed from simply demonstrating whether a target can be detected to ensuring the stability, specificity, and reliability of detection under complex conditions. Table 4 compares the sources of THz information and the major limitations across different agricultural application areas.

**Table 4.** Comparison of THz Detection Characteristics and Key Challenges across Different Agricultural Application Scenarios.

| Application Area | Main THz Response Information | Current Research Characteristics | Major Limitations | Key Research Challenges |
|---|---|---|---|---|
| Seed Quality and Germplasm Screening | Moisture, internal composition, and tissue structure | Extensive studies on seed vigor, purity, stress resistance, and germplasm classification | Variations in cultivar, batch, and moisture content affect model stability | Generalization across cultivars and batches |
| Soil Characterization and Contaminant Detection | Moisture, dielectric properties, and particle scattering | Applications include soil moisture, heavy metals, and microplastics | Coupled effects of moisture, particles, and multicomponent responses | Signal decoupling in complex matrices |
| Monitoring Crop Water Status | Water absorption and dielectric loss | Quantitative single-leaf analysis, spatial imaging, and dynamic monitoring have developed in parallel | Interference from canopy structure and ambient humidity | Scaling from individual leaves to crop canopies |
| Crop Stress and Disease Assessment | Changes in water status, tissue structure, and physiological metabolism | Covers pathogen identification, diseased-tissue detection, and assessment of multiple stress types | Overlapping responses induced by different stresses | Stress-specific identification |
| Agricultural Product Quality Assessment | Moisture, composition, and internal structure | Covers physicochemical parameters, internal defects, structural characteristics, and overall quality assessment | Strong attenuation in high-moisture samples and substantial differences among sample types | Matching detection modalities to sample characteristics |
| Contaminant Detection in Agricultural Products | Molecular responses and dielectric changes | Conventional spectroscopy and metamaterial-enhanced detection are both widely investigated | Trace-level targets are susceptible to interference from complex matrices | Quantitative reliability in real sample matrices |

## 5. Challenges and Future Directions

Representative THz studies on seed assessment [62], soil characterization [103], crop stress evaluation [123], and pesticide detection [157,162] have mainly been conducted

under laboratory conditions, while validation in operational fields, greenhouses, and production lines remains limited. The applicability of THz sensing varies considerably across agricultural targets. Seeds and certain low-moisture agricultural products provide relatively favorable conditions for spectral analysis and internal structure imaging, whereas living leaves, fresh agricultural products, and moist soils are more strongly affected by water absorption and sample heterogeneity. Furthermore, THz responses associated with crop stress and disease may overlap with changes caused by other physiological factors, while the detection of trace contaminants generally requires higher sensitivity and selectivity. These differences indicate that successful detection under laboratory conditions does not necessarily guarantee reliable performance in practical agricultural environments. Three major challenges therefore require further attention: reliable sensing of complex samples, cross-scenario model generalization, and engineering implementation of detection systems [29,166].

(1) Reliable detection and high-sensitivity sensing of complex agricultural samples. Strong water absorption and complex matrix effects are major factors limiting the stability of THz detection in agricultural applications [167]. Water in living leaves, fresh fruits and vegetables, and moist soils can substantially attenuate THz signals, while atmospheric humidity under field conditions may introduce water-vapor absorption and spectral baseline variations. Meanwhile, scattering and dielectric responses arising from soil particles, plant tissues, and heterogeneous structures of agricultural products may overlap with target-specific features, making it difficult to reliably extract weak responses from pesticide residues, pathogenic spores, and contaminants. Importantly, the role of water varies with the sensing objective. Water-related responses provide useful information for plant moisture monitoring but may obscure weaker molecular signatures in chemical and contaminant detection. Similarly, changes in the THz responses of infected plant tissues may reflect variations in water status or tissue structure rather than pathogen-specific characteristics. Therefore, distinguishing target-related information from interfering responses remains essential for improving sensing specificity. Existing spectral preprocessing methods can partially reduce the effects of non-target factors, such as baseline drift and scattering, but cannot fully resolve the coupled interference encountered during in situ measurements. Future studies should further investigate THz propagation mechanisms in agricultural materials and develop environmental compensation strategies to clarify the relative contributions of water, tissue structure, and target constituents to measured signals [168]. In parallel, sensing structures based on metamaterials, metasurfaces, near-field enhancement, and microfluidics warrant further investigation for amplifying weak responses and improving the sensitivity and selectivity of trace-target detection [169]. Beyond demonstrating distinguishable signals under controlled conditions, future evaluations should include real agricultural matrices, independent sample batches, and varying environmental conditions. Detection limits, repeatability, quantitative accuracy, and resistance to matrix interference should be considered when assessing practical sensing performance.

(2) Mechanism-driven intelligent analysis for cross-scenario applications. Machine learning and deep learning have improved feature extraction from THz spectra and images; however, most existing models are developed using specific cultivars, small datasets, and controlled experimental conditions, and their performance may deteriorate when applied to different crop varieties, soil types, or environmental conditions [46]. Moreover, the lack of standardized protocols for instrument parameters, sample preparation, data preprocessing, and model evaluation across studies restricts data sharing and model transferability. Related studies on chemometric modeling and soil sensor calibration have demonstrated that data leakage during preprocessing and validation

may lead to overly optimistic performance estimates [55,56]. This issue is particularly important for agricultural THz data analysis because repeated measurements of the same sample may introduce dependencies between training and test data. Reliable model evaluation therefore requires careful separation of training and test samples, particularly when independent sample sizes are limited [66,67]. Future research should establish standardized agricultural THz data acquisition and evaluation frameworks and expand datasets across cultivars, geographical origins, sample batches, and environmental conditions. Independent validation across batches and sensing scenarios is also needed to assess model robustness.

In model development, physical priors such as the dielectric response of water, low-frequency molecular vibrations, and electromagnetic propagation mechanisms can be incorporated into machine learning and deep learning models to develop analytical approaches jointly constrained by physical mechanisms and data. Meanwhile, existing THz studies have demonstrated the potential of combining spectroscopic and imaging information for agricultural product analysis, providing evidence for the complementary information contained in THz spectra and images [75,76]. Beyond information fusion within THz systems, THz sensing can also be integrated with hyperspectral imaging, near-infrared spectroscopy, machine vision, and thermal infrared sensing to exploit complementary information regarding internal state, chemical composition, and external phenotypes [170–172]. Cross-modal sensing has also been investigated through SERS–THz dual-modal structures for multipesticide detection, illustrating the potential of combining different electromagnetic response mechanisms to improve the discrimination of target substances [80]. Nevertheless, multimodal fusion should be evaluated against single-modality models to determine whether additional sensing information provides meaningful improvements in robustness and generalization. Combined with transfer learning and few-shot learning, these approaches may support the development of more interpretable and transferable models for agricultural applications.

(3) Miniaturized instrumentation and online sensing of agricultural processes. Current agricultural THz studies still rely predominantly on laboratory-based systems such as THz-TDS, which involve complex optical configurations, relatively high costs, and sensitivity to environmental factors such as temperature, humidity, and mechanical vibration, thereby limiting large-scale deployment in field and on-site applications [166]. THz-FDS and solid-state THz devices based on resonant tunneling diodes (RTDs) and complementary metal–oxide–semiconductor (CMOS) technologies provide promising technical routes toward system miniaturization [173–175]. Nevertheless, further improvements are required in output power, signal-to-noise ratio, detection speed, and long-term stability. The requirements for practical deployment also vary among agricultural scenarios. Seed sorting and agricultural product safety screening generally require rapid and repeatable measurements of individual samples, whereas crop water-status monitoring requires stable sensing under changing plant and environmental conditions. Accordingly, the design of THz sensing systems should consider not only detection sensitivity but also measurement time, environmental adaptability, operating cost, and maintenance requirements.

Future efforts should promote the integrated design of THz sources, detectors, enhanced sensing structures, and data-processing modules and develop portable, online, and embedded systems tailored to specific agricultural scenarios. Potential applications include rapid quality sorting during seed production, dynamic monitoring of crop water status and stress during growth, and online screening of quality and safety attributes during agricultural product processing, storage, and transportation. Further integration with the Internet of Things (IoT), edge computing, and intelligent agricultural equipment could

support a continuous sensing framework encompassing information acquisition, data analysis, diagnosis, and decision-making [176,177]. However, the practical feasibility of such systems should be established through long-term operational testing and evaluation under representative production conditions.

Overall, the further development of THz sensing in agricultural engineering requires a transition from laboratory-based demonstrations of signal differences toward reliable, target-specific, and reproducible measurements under practical conditions. Improving sensing sensitivity alone is insufficient without addressing the physical interpretation of THz responses, model transferability, and system adaptability. Future progress will therefore depend on coordinated advances in sensing mechanisms, mechanism-informed data analysis, and application-oriented instrumentation.

## 6. Conclusions

This review summarizes advances in terahertz (THz) sensing mechanisms, intelligent data analysis, and agricultural applications. The sensitivity of THz waves to water, molecular vibrations, and tissue dielectric contrasts provides a physical basis for the nondestructive characterization of agricultural materials. THz spectroscopy and imaging have demonstrated potential in seed quality assessment, soil characterization, crop water-status monitoring, stress and disease detection, and agricultural product quality and safety evaluation, although the maturity of these applications varies considerably.

The integration of chemometrics, machine learning, deep learning, and multimodal information fusion has improved the interpretation of complex THz data and expanded its analytical capabilities. However, reliable sensing requires not only accurate models but also an understanding of the underlying electromagnetic responses and validation across different samples and measurement conditions.

Overall, THz sensing provides a complementary approach to nondestructive information acquisition in agricultural engineering. Its transition from laboratory research to practical applications will depend on coordinated improvements in sensing reliability, model generalization, and system integration, supporting its potential use in intelligent agricultural monitoring and quality assessment.

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selection of literature, evaluation of scientific evidence, interpretation of previous studies, identification of research gaps, and formulation of the conclusions were performed and verified by the authors. Generative AI was not used to generate original experimental data or independently conduct scientific interpretation. All AI-assisted text was reviewed and revised by the authors, who take full responsibility for the content of this publication. In addition, ChatGPT (GPT-6, OpenAI) was used to assist in generating selected conceptual graphical elements for Figure 2, Figure 4, and Figure 5. These elements were subsequently edited and refined by the authors using Adobe Photoshop. The authors reviewed and verified all AI-assisted graphical content and take full responsibility for its scientific accuracy, originality, and integrity.

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