Review of the application of in-situ sensing techniques to address the tea growth characteristics from leaf to field

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Abstract: The tea plant is a valuable and evergreen crop that is extensively cultivated in China and many other countries. Currently, there is growing research interest in this plant. For the tea industry, it is crucial to develop rapid and non-invasive methods to evaluate tea plants in their natural environment. This article provides a comprehensive overview of non-invasive sensing techniques used for in-situ detection of tea plants. The topics covered include leaf, canopy, and field-level assessments, as well as statistical analysis techniques and characteristics specific to the research. Non-invasive testing technology is primarily used for monitoring and predicting tea pests and diseases, monitoring quality, and nutrients, determining tenderness and grade, identifying tea plant varieties, automatically detecting, and identifying tea buds, monitoring tea plant growth, and extracting tea garden areas through remote sensing. It also helps to evaluate planting suitability, assess disasters, and estimate yields. Additionally, the article examines the challenges and prospects of emerging techniques aimed at resolving the in-situ detection problem for tea plants. It can assist researchers and producers in comprehensively understanding the tea environment, quality characteristics, and growth process, thereby enhancing tea production quality, and fostering tea industry development.

Keywords: non-destructive, in-situ detection, tea plants, growth characteristics, sensors
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1 Introduction

Tea is a beneficial beverage due to its compounds such as tea polyphenols, amino acids, and vitamins, which possess medicinal qualities[1]. Tea plants are extensively cultivated, and farms are distributed globally. The tea garden ecosystem is a controlled semi-artificial ecosystem that is distinct from agricultural and woodland ecosystems. It has a great capacity for absorbing carbon and makes a significant contribution to reducing carbon emissions. Traditional detection methods for tea plants rely heavily on manual labor and are often subject to. For example, tea range and yield are currently monitored by collecting census data and conducting field surveys, while tea quality and growth estimation are mainly through manual identification or chemical analysis. These results are often inconsistent and less objective[2]. In recent years, non-destructive detection techniques such as remote sensing image resources (RSI), near-infrared spectroscopy (NIRS), hyperspectral imaging (HSI), synthetic aperture radar (SAR), and digital cameras have enabled rapid detection of tea plants.

Remote sensing is a powerful tool for monitoring tea plants and their environment. It provides timely, cost-effective, and large-scale information on tea plants, without requiring direct contact. Multispectral satellite sources are often used to monitor the distribution of tea gardens[3]. The Vis/NIR spectra between 400 to 2500 nm can be used to analyze vegetation status by studying the absorption of the atomic groups[4] and predicting related components. Numerous studies have focused on the quantitative analysis of chemicals present in tea, such as caffeine[5], tea polyphenols[6], and amino acids[7] using different NIRS apparatus. Technologies that involve mechanics, optics, electromagnetic sensing, digital video, and image processing can provide objective and accurate information for assessing tea quality, and enhancing tea production efficiency[8].

Recently, there has been extensive research on in-situ monitoring of tea plants using non-destructive techniques to evaluate their quality and nutritional value. Chen et al.[4] provided a summary of the application of NIRS, EN, ET, and computer vision techniques for this purpose, while Zhu et al.[9] focused on the use of NIRS alone. Lin et al.[10] reviewed various vibrational spectroscopic techniques, including NIR, MIR, Raman, terahertz (THz) spectroscopy, and HSI technologies, for tea quality and safety analysis. These methods, combined with machine learning and neural networks, have the potential to quantitatively predict tea quality components and evaluate tea safety. Despite several reviews, there has been no discussion on in-situ detection for tea plant monitoring. Based on existing research, this review aims to fill that gap by evaluating the use of these non-destructive techniques for in-situ monitoring of tea plants at various scales, as shown in Figure 1.

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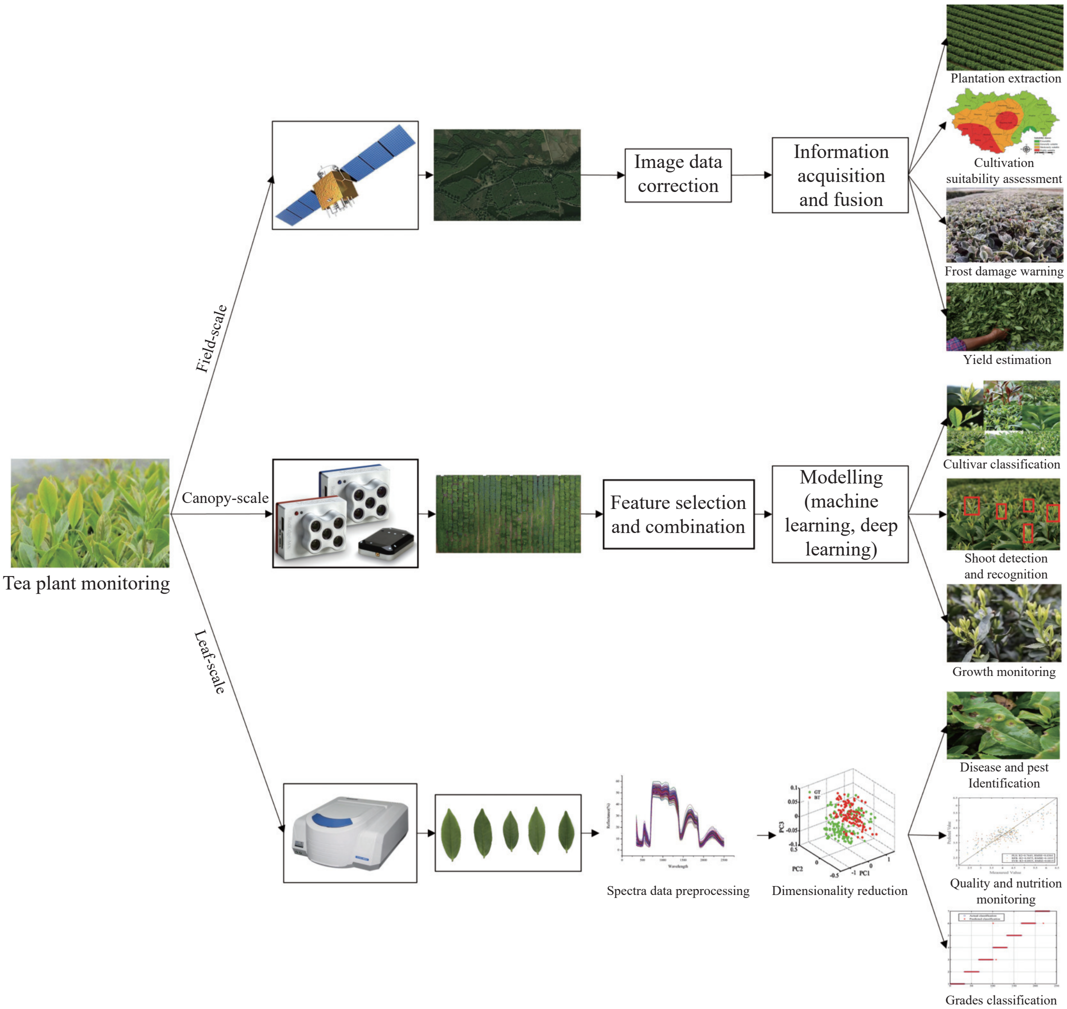

Figure 1 Tea plants monitoring by in-situ techniques in different scales

2 Leaf-scale monitoring for tea quality and stress

To ensure optimal tea quality and detect tea leaf stress, sensors are utilized to measure the physical and chemical properties of tea leaves, including nutrition, grades, and other parameters. These sensors can also identify the specific diseases and pests affecting the tea leaves. Figure 2 illustrates the significant role of leaf-scale monitoring in the tea plant.

2.1 Disease and pest identification of tea

Due to a lack of experienced tea plant protection experts and environmental data, tea growers may struggle to accurately diagnose diseases and pests. It is a significant issue for the tea industry, which requires precise identification to maintain yield and production quality. One solution to this problem is the use of computer vision systems and deep learning models[11]. For instance, Li et al.[13] proposed using a four-channeled residual network (F-

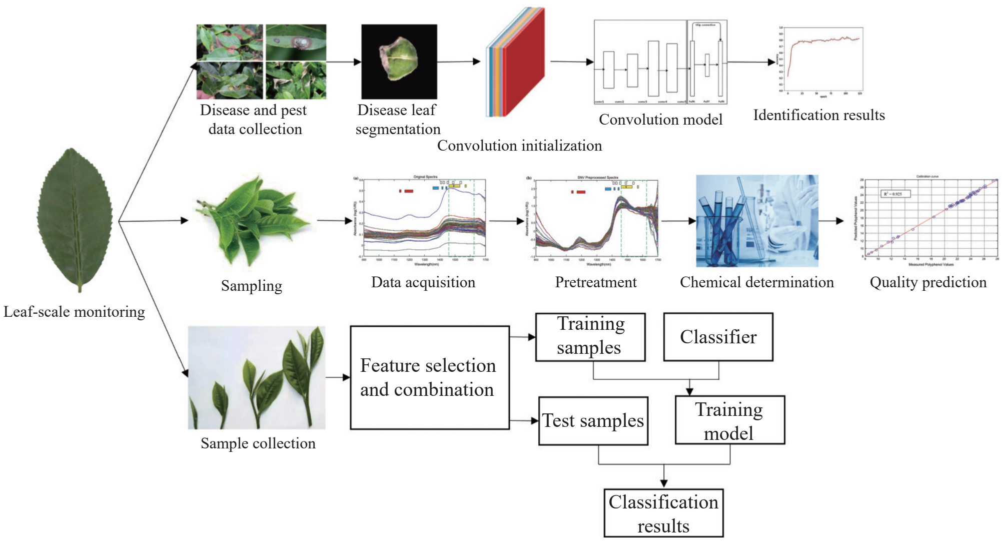

Figure 2 Technique role of tea plant monitoring on leaf-scale[6,11,12]

RNet) based on R-CNN and wavelet trans-form on RGB images to identify the diseases and pests of tea leaves. Karmokar et al.[14] developed a tea leaf disease identifier that integrates a neural network to recognize diseases by extracting features from tea leaf images. Additionally, HSI is effective for tea plant phenotyping and insect infection identification. Researchers have used HSI to detect tea anthracnose[15] and other tea diseases and pests by combining wavelength analysis with HSI data[16]. There are also non-destructive techniques available for identifying tea diseases and pests which are listed in Table 1.

Table 1 Tea disease and pest identification techniques

Detection system	Disaster type	Algorithms	Results	References
Digital camera	Tea blight	Deep Hashing with Integrated Autoencoders	98.50%	[11]
		GBM	77.00%	[17]
	Tea white scab, tea leaf blight, tea red scab, and tea sooty mould	CNN MergeModel	94.00%	[12]
	Brown blight, target spot, and tea coal diseases	Mask R-CNN, wavelet transform, and F-RNet	88.00%	[13]
	Tea red scab, tea red leaf spot, tea leaf blight	SVM-C-DCGAN-VGG16	90.00%	[18]
	Tea leaf blight, tea bud blight, tea red scab.	CNN	92.50%	[19]
	Brown blight, gray blight, helopeltis, and red spot	Deep CNN	96.56%	[20]
	Red rust, red spider, thrips, helopeltis, and sunlight scorching	NSGA-II-PCA-SVM	83.00%	[21]
	Tea anthracnose, tea brown blight, tea netted blister blight, *Exobasidium vexans* massee, *Pestalotiopsis theae*	SLIC-SVM	96.80%	[22]
Hyperspectral imaging	Tea anthracnose	ISODATA and two-dimensional (2D) thresholding classification	96.00%	[15]
	Tea green leafhopper, anthracnose, sunburn, insect stress	Wavelet analysis, RF	The overall accuracies are respectively 93.99%-94.20%, 94.12%-94.28%, and 82.50%-83.91%.	[16]
	Tea stalks and insect bodies	LDA	97.56%	[23]
Electronic nose	Tea pest damage severity	PCA-MLP	100%	[24]

Note: GBM: gradient boosting machine, CNN: convolutional neural network, DCGAN: deep convolution generative adversarial networks, NSGA: non-dominated sorting genetic algorithm, SLIC: simple linear iterative cluster, SVM: support vector machine, RF: random forest, LDA: linear discriminant analysis, PCA: principal component analysis, MLP: multi-layered perceptron.

2.2 Tea quality and nutrition monitoring

Traditionally, the quality and nutritional value of fresh tea leaves have been assessed through sensory evaluation by experienced tasters, which is not always reliable. To address this issue, various nondestructive methods have been developed to control the quality of tea leaves. These methods detect tea polyphenols[25], caffeine, nitrogen, phosphorus, potassium, chlorophyll, and moisture. Furthermore, machine learning and deep learning techniques have been utilized to estimate tea quality content from HSI, multispectral, and NIR information. The combination of nondestructive techniques with chemometrics or machine learning methods has been successful in determining tea leaf quality and nutrition. For instance, Wang et al.[26] utilized the hyperspectral technique in conjunction with SPA-MLR to estimate the moisture, total nitrogen, and crude fiber contents of fresh tea leaves. Sun et al.[27] used NIR-HSI to visualize the distribution of moisture content in tea leaves. Zhang et al.[28] predicted the moisture content of tea leaves through the NIRS technique. A detailed summary of the related research is listed in Table 2.

Table 2 Summary of non-destructive methods used for tea quality and nutrition monitoring

Detection techniques	Components	Analysis methods	Results	References
Hyperspectral	Chlorophyll	KELM	The PRD was from 1.4 to 2.0	[29]
		PLSR	R=0.9337 (a), 0.9322 (b), 0.9333 (total).	[30]
		DBN	The RPDs were always larger than 1.4.	[31]
		KELM	RPD values from 3.38 to 5.92 for the test set.	[32]
	Nitrogen	ROI-PCA-SVM	100%	[33]
		PLSR	R^2=0.924	[34]
	Phosphorus and potassium	SPA-MLR	R^2=0.9423 (P) and 0.9168 (K)	[35]
	Carotenoid	Calibrated PROSPECT–D	R^2=0.793	[36]
		Standard curve and 2D Raman fast scans.	The results were similar with HPLC.	[37]
		PLSR	R=0.9036	[30]
NIR	Polyphenols	PLS	R^2=0.95	[6]
	Catechins	SPA, LS-SVM	R^2=0.996, 0.991, 0.997, and 0.988 of EGC, EGCG, EC, and ECG	[38]
		CARS-SPA-PLS	R^2= 0.949, 0.893, 0.968, and 0.931 of EGCG, ECG, EGC, and EC	[39]
	Caffeine	CARS-SPA-MLR	R^2=0.917	[39]
	Nitrogen	PLSR based on EPO and VCPA-IRIV	R^2=0.9371	[40]
	Moisture	DWT-BOSS-PLS	R_c^2=0.9410, RMSEC=0.2404; R_{cv}^2=0.9171, RMSECV=0.2851; R_p^2=0.9513, RMSEP=0.2236	[28]
		SG-MSC with CARS-SR	R^2=0.8631, RMSEP=0.0163	[27]

Note: KELM: kernel extreme learning machine, PLSR: partial least squares regression, DBN: deep belief network, ROI: region of interest, SPA: successive projections algorithm, MLR: multiple linear regression, LS-SVM: least squares-support vector machines, CARS: competitive adaptive reweighted sampling, EPO: external parameter orthogonalization, VCPA-IRIV: variable combination population analysis- iteratively retaining informative variables, DWT: discrete wavelet transforms, BOSS: bootstrap soft shrinkage, SG: Savitzky-Golay, MSC: multiplicative scatter correction, SR: stepwise regression.

2.3 Tea tenderness and grades classification

The freshness of tea leaves is crucial in producing high-quality tea. Processing tea to a standard requires accurately determining the freshness of the leaves. A variety of factors can affect the tea quality, including their growing surroundings, position on the plant[41], and time of harvest[42]. Tea leaf images provide valuable biological information such as leaf shape, size, and edges, which can be used to differentiate tea grades, varieties, and tenderness. Tang et al.[43] proposed a method for sorting green tea leaves based on texture extraction using non-overlapping window local binary patterns (LBP) and gray level co-occurrence matrix (GLCM). This approach has been successfully employed in the automatic tea processing lines to capture tea leaves from conveyor belts. Additionally, Zhang et al.[37] introduced a non-invasive Raman spectroscopy scanning method to evaluate the tenderness of fresh tea leaves. Table 3 compiles various non-destructive approaches for a range of tea-related classifications, e.g., tea grade, leaf position, variety, geographical origin, and harvest season identification.

3 Canopy-scale growth monitoring by optical sensors

The quality of tea products is influenced by the cultivars, growing conditions, and processing techniques used. In tea gardens, the raw materials used in tea production are crucial in determining the highest potential quality of tea. Therefore, it is essential to monitor tea plant growth accurately and quickly on a field scale. Optical sensors are a valuable tool that can measure various aspects of the tea plant canopy, such as its structure, color, and shape, as well as the amount of light, water, and nutrients it receives, and the level of photosynthesis taking place. This information can be used to optimize tea plant growth by efficiently allocating resources and ensuring optimal conditions. Figure 3 shows the significance of canopy-scale monitoring of tea plants.

Table 3 Summary of non-destructive methods in tea grades classification

Properties of study	Detection techniques	Analysis methods	Results	References
Leaf grades/ tenderness	Imaging technology	LBP and GLCM	95.33%	[43]
	Vis/NIR spectrum	PSO-SG -SVM	98.92%	[44]
Leaf position	Vis/NIR spectrum	PCA -LDA	100%	[39]
Leaf variety	Vis/NIR	PCA -LDA	98.15%	[39]
	FTIR	PLS-SOM	100%	[45]
	Imaging	variational autoencoder -FCN	83%	[46]
Geographical origin	FT-IR fingerprinting	PCA-LDA	98.0%	[47]
Harvest season	FT-IR fingerprinting	PLS-DA	100%	[48]

Note: PSO: particle swarm optimization, SOM: self-organizing maps, FCN: fully convolutional networks, DA: discriminant analysis.

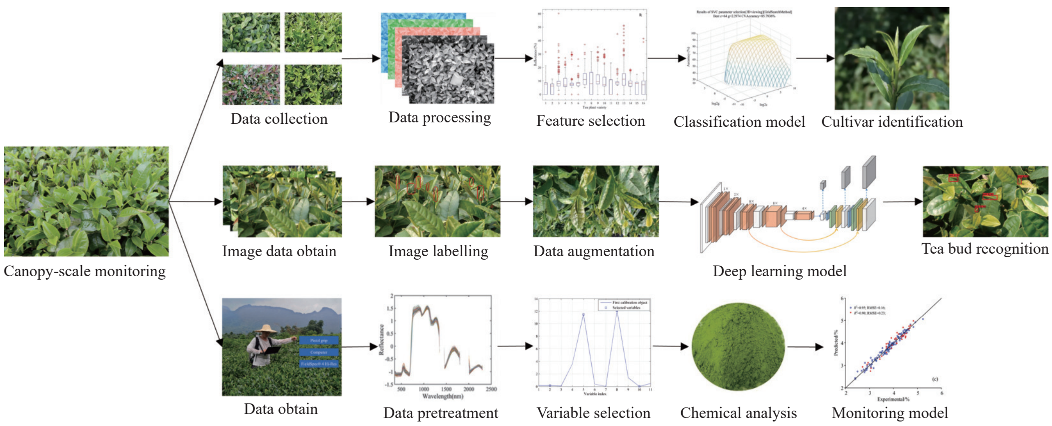

Figure 3 Technique role of tea plant monitoring on canopy-scale[49]

3.1 Tea cultivar classification

The yield, quality[50], resistance, and flavor of tea plants can differ significantly depending on the variety being grown. Moreover, different cultivars have different responses to vegetative and reproductive growth[51]. The appearance of different tea cultivars, including the color and texture of the shoots, leaves, plant shape, yield, and bloom of one bud with one or two leaves, is evaluated by experts. However, identifying different tea cultivars is a complex and challenging task that currently depends on DNA sequencing analysis[52] or empirical experts. Each tea cultivar is suited to different tea products. For instance, Fuding dabai is ideal for Baimudan, while Longjing 43 is excellent for Longjing tea processing. Over the last two decades, reflectance spectra classification has been used increasingly to determine tea plant species, as Nidamanuri[53], used hyperspectral data to differentiate nine tea plant varieties and six other natural plants in a tea garden. Cao et al.[54] deployed multispectral imaging technology to discern 16 high-yield tea plant cultivars, and Tu et al.[55] used UAV-HSI to classify tea cultivars based on canopy information. Table 4 lists insight into the research that scientists have conducted to classify tea cultivars and recognize tea plants using rapid and non-destructive methods.

Table 4 Summary of non-destructive methods used for the classification and recognition of tea plant cultivars

Detection techniques	Analysis methods	Results	References
Hyperspectral	*k*-NN, LDA, SVM, ANNs, MLC, NS	70% to 80%	[53]
	SVM	100%	[56]
	MLC, MDC, ANN, SVM	MLC: 89.4% MDC: 80.4% ANN: 93.2% SVM: 96.2%	[55]
Vis/NIR	PLS and Euclidean distance	90.3% (calibration set), 83.5% (test set)	[57]
	WT, PCA, and ANN	77.3%	[58]
	BPLS-DA	100% (calibration set), 98% (prediction set)	[59]
FTIR	PLS-SOM	100%	[45]
Multispectral camera	SPA-SVM	97.00% (training set), 90.52% (test set), 88.67% (validation set)	[54]

Note: *k*-NN: *k*-nearest neighbor; ANNs: Artificial neural networks; MLC: Maximum likelihood classifier; NS: normalized spectral similarity score; MDC: Minimum distance classification; WT: Wavelet transform; BPLS-DA: Boosting partial least-squares discriminant analysis.

3.2 Tea shoot detection and recognition

Mechanical and automatic tea picking is essential for tea plantations due to the high cost and labor-intensive nature of traditional manual tea harvesting. Tea shoot detection and recognition in real-time is necessary. However, detecting tea shoots can be challenging due to the complex lighting conditions and numerous canopy structures. The traditional image processing approach uses shape, color, and texture algorithms for tea shoot recognition. Using a fusion of traditional image processing algorithms along with deep learning techniques has enhanced the accuracy of tea shoot detection. Several approaches, such as edge detection[60], improved deep convolutional encoder-decoder network[61], faster R-CNN and FCN techniques[62], RGB-D camara[63], and two-level fusion network[64], have been proposed for tea shoot detection and recognition. YOLOv3 has become a widely adopted computer version system for tea shoot recognition[49]. Table 5 lists the commonly used techniques and algorithms for tea shoot detection.

Table 5 Tea shoot detection technique and algorithms

Detection system	Algorithms	Results	References
VRS (Consists of two global cameras and one local camera)	YOLOv3	One: 0.84-0.89, Two: 0.52-0.62, Side: 0.76, Top: 0.79	[64]
Computer version system	YOLOv3	83%	[49]
	Bayesian discriminant principle	90.3%	[65]
Digital camera	YOLOv3 and DenseNet201, the learning rate is 0.0001, the optimizer is sgdm, validation frequency is 48.	95.71%	[63]
	MR3P-TS	0.949	[66]
	Faster R-CNN, FCN	Faster R-CNN: 79%, FCN: 84.91%	[62]
	Improved watershed algorithm	95.79%	[60]
	DP network	92.8%	[67]
	TS-SegNet	0.89	[61]
	Improved YOLOv3	93.06%	[68]
RGB-D camera	YOLOv3	93.1%	[69]
Multispectral Imaging	Deep Label Distribution Learning (multiple VGG-16 and auto-encoding network)	MAE=0.68	[70]
Smartphone	Mask R-CNN	93.95%	[71]

Note: MR3P-TS: mask R-CNN positioning of picking point for tea shoots, DP: discriminative pyramid, TS-SegNet: tea sprouts segmentation based on improved deep convolutional encoder-decoder network.

3.3 Tea plant growth monitoring

Monitoring the growth of tea plants involves using digital and spectral information platforms to collect images and textures of the tea canopy. These images are then used to create quantitative models of tea quality, nutrients, and pigments using statistical analysis, machine learning, or deep learning algorithms. For instance, some studies have used multivariate analysis with hyperspectral data to predict polyphenols[47], nitrogen[72], chlorophyll[31], and plant behaviors under different management practices[73]. Other studies have utilized various imaging systems to evaluate tea quality components or diagnose tea plant stress. Kang et al.[74] applied the HSI to estimate the catechins content of fresh tea leaves in green tea fields and achieve 0.79 precision. Cui et al.[75] detested the tea plant stress using HSI. Chen et al.[76] deployed a multispectral imaging system to evaluate tea quality components with 0.85 accuracies at a canopy level. Wang et al.[77] developed a smartphone-based micro near-infrared spectrometer system to diagnose tea pigments. Cao et al.[78] combined multispectral images and hyperspectral data of tea plant canopy to predict nitrogen content. Luo et al.[79] employed UAV image data of the tea plant canopy to monitor polyphenols, nitrogen, and amino acid contents. Tu et al.[55] utilized a hyperspectral camera mounted on a UAV to monitor the tea polyphenols and amino acids of tea plants and achieved good accuracy. Real-time monitoring of tea growth through these technologies provides support for improving the information management level and intelligent operation of tea gardens. In the future, thermal infrared and mid-infrared imaging technology may also be used to monitor tea plants.

4 Field-scale monitoring for scientific tea garden management

The tea plantation industry plays a crucial role in the development of rural economies in China. To effectively monitor and evaluate tea gardens, field-scale monitoring of tea plants is essential. By swiftly extracting information from tea planting areas, this technique aids in monitoring tea growth, predicting disasters, and estimating tea yield. Furthermore, it assists in optimizing the use of tea garden resources and leveraging the exceptional ecological geological environment. Figure 4 displays the procedural steps for conducting field-scale monitoring of tea plants.

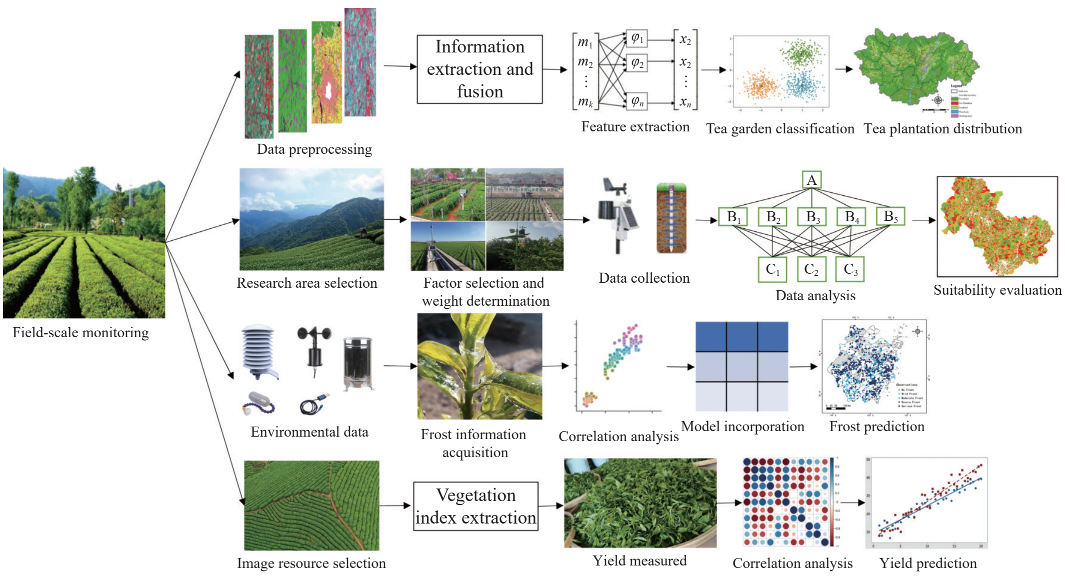

Figure 4 Technique role of tea plant monitoring for scientific tea garden management[80,81]

4.1 Tea plantations extraction and dynamic changes evaluation

Accurately obtaining the dynamic distribution and planting area of tea plants is crucial for the government to evaluate the tea industry. Due to the unique texture features of tea gardens, high-altitude remote sensing via satellite can effectively monitor them[82]. Several studies have utilized high spatiotemporal-resolution multispectral imagery to evaluate the spatial distribution and area of tea plantations, including Li et al.[83], Huang et al.[84], and Dihkan et al.[85] Various satellite resources, such as Sentinel-2[3] and WorldView-2[86], have been used to examine the distribution and extraction of tea plantations. In addition, remote sensing technologies such as Landsat[87], SAR[88], Lidar[89], and hyperspectral data[90] are also utilized for tea garden classification. When applying remote sensing technology to tea plantation extraction, color, texture, spectral, and terrain features are considered, including NDVI[86,91], MNDVI[85], EVI[88], MNDWI[88], LSWI[88], GLCM texture[86], Gabor texture[86], DEM[88]. Furthermore, machine learning or deep learning methods coupled with multiple remote sensing technologies have been used to differentiate tea cultivars from other vegetation. Table 6 provides a summary of various non-destructive remote sensing data sources used for tea plantation extraction.

Table 6 Summary of in-situ detection methods in tea plantation evaluation

Method	Data type	Spatial resolution/m	Feature	Application
Time series data	MODIS	250 (1-2 bands) 500 (3-7 bands) 1000 (8-36 bands)	Data storage is efficient, spectrum range-wide, and data reception is simple and free.	[92]
	Sentinel-2/Sentinel-1	10, 20, 60	Red edge range has three bands, effective in monitoring vegetation health.	[3, 93-95]
Multispectral data	GF-1/GF-2/GF-5	2 (Panchromatic) 8 (Multispectral) 16 (Multispectral)	High and medium spatial resolution earth observation and large width imaging.	[89, 96, 97]
	Worldview-2	0.5 (Panchromatic) 1.8 (Multispectral)	Takes pictures faster, and more accurately and provides high-resolution images in multiple bands. Color band analysis supports plant identification and analysis, and analysis of plant growth reveals plant health status.	[86]
	Landsat	15-60	Long time series, high accuracy, and large data volume.	[87, 88]
Hyperspectral data	CASI-1500	0.2-1.5	Small detector, embedded programmable controller, high signal-to-noise ratio, and high-performance optical components for vegetation classification and agricultural monitoring.	[90]
LiDAR data	Optech ALTM, SAR	--	Integrated imaging sensor options, rapid coverage, data output capability, unrestricted bank-angle, high data accuracy and integrity, and intensity capture with large dynamic range for exceptional lidar image quality.	[89, 90]
SAR data	PALSAR-1	10	Contributions to cartography, precise regional land cover assessment, disaster monitoring, and resource surveys.	[88]
Google Earth	Google earth image	0.27-71 000	Fast access speed, reliable data, high coverage rate, and promptness.	[76]

Note: MODIS: Moderate-resolution imaging spectroradiometer, GF: Gaofen, LiDAR: Light detection and ranging, SAR: Synthetic aperture radar, PALSAR: Phased array L-band synthetic aperture radar.

4.2 Tea cultivation suitability assessment by remote sensing and spatial analysis

The production and quality of tea are heavily reliant on various environmental factors, including soil suitability, precipitation, temperature, and moisture[98]. Assessing the suitability of tea plant growth is crucial for establishing a successful tea plantation[99]. The geographical origins of tea produce varying flavors and tastes due to diverse factors such as climate, environment, altitude, soil, and topography. It is vital to identify the optimal climate and soil to guarantee the suitable growth and harvesting of tea. Previous studies have employed various methodologies, including the Delphi method and GIS[100], Sentinel-2 image data[81], and integrating Sentinel-2 images with GIS[101] to evaluate tea plantation suitability. Factors considered for tea cultivation suitability include climate[102], soil[103], terrain, human-related factors, ecological economy factors, and tea plant growth information[104]. Accurate regional demarcation and assessment of tea plantations can significantly enhance tea planting, boost tea quality, and provide a scientific basis for tea cultivation.

4.3 Frost damage warning of tea plants

Tea cultivation is often hampered by cold and frost which can significantly lower yields and deteriorate tea quality[105]. To prevent and manage such occurrences, it is critical to conduct a phenological analysis of tea gardens. This analysis can assist the agricultural department in improving preparedness. Kimura et al.[106] demonstrated a spatiotemporal distribution of the thermal effects of frost-protective fans in a tea field by modeling the cold tolerance of tea buds based on temperature patterns[107]. Additionally, they proposed a sensible assessment of tea frost risk, using 1 km^2-gridded meteorological data[108]. Kotikot et al.[92] utilized MODIS-derived LST to detect frost occurrences in tea plantations, and further employed MODIS and risk factors associated with topography and land surface temperature[109]. Wu et al.[110] put forth a real-time forecasting system for evaluating frost damage degrees by using a small weather station to validate parameters, resulting in accurate prediction of the frost damage. Wang et al.[111] monitored and assessed spring frost in tea plants in China through MODIS data and established a minimum temperature (Tmin) elevation model based on reconstructed MYD11A1 nighttime LST values for 3×3 pixel windows and digital elevation model data[112]. They integrated the satellite-based Tmin estimates and ground-based Tmin observations to analyze the spring frost damage of tea plants from 2003 to 2020 in China, which offers effective guidance for farmers. Xu et al.[80] developed a frost-hazard warning system by combining topography, meteorology, longitude, latitude, and machine learning models in the Zhejiang Province of China. It is essential to conduct monitoring research on tea plant frost to determine the occurrence and degree of damage. Analyzing the distribution of tea frost can serve as a reference for frost prevention and guidance for adjusting tea planting planning and layout.

4.4 Tea yield estimation

Accurately estimating agricultural yield is essential for decision-making regarding prices, exports, and imports, as well as increasing food security and ensuring a sufficient food supply[113]. Tea yield is influenced by various factors, including crown density, and can be determined by remote sensing imagery. Several studies have utilized different satellite information and models to estimate tea yield, including the use of SPOT-7 and ALOS AVNIR-2 images[114], multi-temporal MODIS NDVI data[115], RF model with SVR-based feature selection[116], IRS-1C images[117], SAVI extracted from Landsat-8 OLI and Sentinel-2B images[118], and the FAO AquaCrop simulation model[119]. A summary of the data resources, models, analysis methods, and results of tea yield estimation is provided in Table 7.

Table 7 Common non-destructive methods for tea yield estimation

Type of satellite images	Vegetation Index	Methods	Results	References
Landsat	SAVI	Correlation and regression analyses.	Correlation value is 0.57.	[118]
Sentinel-2	SAVI	Correlation and regression analyses.	Correlation value is 0.67.	[118]
	NDVI	Regression analysis.	2017: R^2=0.69; 2018: R^2=0.66; 2019: R^2=0.67.	[101]
	LAI	Regression analysis.	2017: R^2=0.68; 2018: R^2=0.65; 2019: R^2=0.63.	[101]
SPOT 7 and ALOS AVNIR-2	NDVI	Linear spectral mixture analysis.	35.65%	[115]
MODIS	NDVI	RF, SVM, TLRM	From 2009 to 2018, the RF model R^2=0.73, SVM 0.66, and 0.57 with the TLRM. In 2015 with an R^2≥0.87 by RF.	[115]
IRS-1C	NDVI, SR, TVI	Regression analysis.	NDVI: R^2=0.69; SR: R^2=0.73; TVI: R^2=0.83.	[118]
	NDVI		R=0.760	[120]
MERRA-2 satellite	RH2M, GWT, GWP, GWR, QV2M, ASW, PRE, T2M2, TS	DRS-RF	R=0.933	[116]

Note: SAVI: soil-adjusted vegetation index, NDVI: normalized difference vegetation index, SR: simple ration, LAI: leaf area index, TLRM: traditional linear regression model, TVI: transformed vegetation index, RH2M: relative humidity at 2 m, GWT: surface soil wetness, GWP: profile soil moisture, GWR: root zone soil wetness, QV2M: specific humidity at 2 m, ASW: all-sky surface longwave downward irradiance, PRE: precipitation corrected, T2M2: temperature at 2 meters minimum, TS: earth skin temperature, DRS: dragonfly optimization and support vector regression.

5 Discussion

In the past decade, research into the monitoring of tea plants using non-destructive methods has increased, and considerable results have been obtained. In-situ detection has gained extensive research attention and has become a popular subject in the tea industry and market. Several commonly used non-destructive techniques share advantages including rapid, efficient, and convenient. However, each technique has its own specific advantages and disadvantages when applied to address various issues concerning tea plants.

5.1 Limitations of tea quality at leaf-scale

Monitoring of tea growth and stress of tea at a leaf scale is limited in its ability to detect stress on a large scale. To establish a reliable model for monitoring tea quality, a wide and representative range of leaf samples must be collected. The dynamic monitoring of tea quality is challenged by the fluctuation of water content in fresh leaves. The classification of tea tenderness and grade is also affected by overlapping leaves. Identifying the grade of stacked leaves and determining the proportion of different grades remains a difficult problem to solve.

5.2 Difficulties in tea growth monitoring at canopy-scale

Sensors are commonly utilized to capture the spectral images of the tea plant canopy. However, the accuracy of monitoring tea plant growth is contingent on various factors, including the density of tea germination, bud, and leaf tenderness, and the collection area. Non-destructive testing technology is essential due to the significant impact of water and fertilizer status, as well as the water content of tea leaves, on the quality components. While canopy-scale monitoring provides a comprehensive view of tea plant growth and quality, it may not immediately detect the effects of micro-environments on growth. Furthermore, outdoor light can cause errors in the model's accuracy by interfering with spectral information. The tea bud recognition environment is complex and can be affected by overlap, occlusion, light shadow, species, and tenderness, all of which can affect the outcome.

5.3 Uncertainty of tea garden area extraction and yield estimation by remote sensing images

Utilizing remote sensing images is a valuable approach for identifying tea planting areas on a large scale and obtaining information on the spatial distribution and planting area of tea plants in a dynamic and continuous manner. However, conducting field investigations can be challenging due to the extensive distribution of tea gardens and mountainous planting areas. The accuracy of identifying tea gardens with images can also be affected by various factors such as terrain, weather, and other vegetation in the area, resulting in limited extraction of single source data. Various studies employ distinct remote sensing data sources and classification techniques to extract tea plantations in different regions. Despite exhibiting favorable recognition precision, the outcomes of these studies cannot be compared, making it challenging to assess the impact of integrating diverse data sources and classification methods. Therefore, multi-source remote sensing data and time series data, integrated intelligent algorithm has become a growing trend for extracting tea plant information at a large scale. The yield of tea is influenced by various factors including picking frequency, natural disasters, pests, freezing damage, and drought damage, which pose difficulties for the dynamic monitoring of yield. Moreover, judging the changes in tea plantations before and after picking by remote sensing images is more challenging due to the influence of weather conditions.

6 Conclusions and future trends

In this review, we have comprehensively summarized the latest developments in non-destructive techniques for numerous aspects of tea plant monitoring. Multispectral satellite images are frequently used in tea field-scale monitoring due to their capability to provide a broad range of data from tea gardens quickly and inexpensively. NIRS is the most used method for canopy-scale and leaf-scale monitoring of tea, likely due to the simple preprocessing procedure of NIRS data compared to complex imaging data. Significantly, many investigations have begun to focus on the in-situ detection of tea. Despite the expansive literature on non-invasive techniques and their impressive effectiveness, a compatible model with economical sensors is still absent for tea cultivation and production.

Comprehensive control of the climate conditions and growth status of tea plants is essential to provide basic support for precise regulation of tea plant growth. The combination of the above three scales monitoring, including tea garden identification, tea yield monitoring, tea pest and disease identification, tea quality determination, and tea plant classification, can present the growth trend of tea plants and the appearance of tea gardens in real-time. By predicting the occurrence of tea garden pests, diseases, and natural disasters, it provides data support for tea farming activities and tea garden regulation. Using integrating the data from the leaf, canopy, and tea garden scales, a tea quality detection model can be established. This model can predict tea quality status based on factors such as the growth environment, growth status, and expansion history of the tea plant, and provide corresponding recommendations and adjustment plans.

Apart from the techniques discussed in this review, some other techniques are currently adopted in the field. Raman spectroscopy[121] and nanosensor techniques are widely used to detect hazardous substances, pollutants, pesticide residues[122], and food additives, and have recently been applied to assess authenticity and adulteration in the tea industry. Indeed, these techniques have been used to classify tea types with varying levels of contamination or identify the degrees of adulteration, as well as other tea plant monitoring issues[37]. Moreover, material thermal imaging technology has been employed to measure the thickness and distribution of tea plants, leaf venation tendencies, and micro homogeneity by using the heat waves generated from the interior or surface of leaves. Thermal imaging technology can provide visual images of tea leaves, which can be utilized for the monitoring of tea leaves obtained from different cultivars. The benefits of using a combination of various analysis methods to detect tea plants in situ will be considerable compared to using one method alone. Furthermore, the use of portable apparatus and sensors that can be connected to smartphones is expected to increase soon. Additionally, the combination sensors of different scales, such as canopy scale and field scale, can complement each other to improve tea characteristics monitoring. It is anticipated that intelligent sensory technology combined with various sensors that can replicate the sensory judgments of tea experts will become a reality. We hope this review will furnish those working in tea fields with helpful information and will offer a beneficial and convenient resource for the in-situ and non-destructive observation of tea plants.

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[References]

[1] Chen T T, Yang C S. Biological fates of tea polyphenols and their interactions with microbiota in the gastrointestinal tract: implications on health effects. Critical Reviews in Food Science and Nutrition, 2020; 60(16): 2691–2709.

[2] Zhu H K, Ye Y, He H F, Dong C W. Evaluation of green tea sensory quality via process characteristics and image information. Food and Bioproducts Processing, 2017; 102: 116–122.

[3] Chen P P, Zhao C J, Duan D D, Wang F. Extracting tea plantations in complex landscapes using Sentinel-2 imagery and machine learning algorithms. Community Ecology, 2022; 23: 163–172.

[4] Chen Q S, Zhang D L, Pan W X, Ouyang, Q, Li H H, Urmila K, et al. Recent developments of green analytical techniques in analysis of tea's quality and nutrition. Trends Food Science & Technology, 2015; 43(1): 63–82.

[5] Sun Y M, Wang Y J, Huang J, Ren G X, Ning J M, Deng W W, et al. Quality assessment of instant green tea using portable NIR spectrometer. Spectrochim Acta A:Molecular and Biomolecular Spectroscopy, 2020; 240: 118576.

[6] Hazarika A K, Chanda S, Sabhapondit S, Sanyal S, Tamuly P, Tasrin S, et al. Quality assessment of fresh tea leaves by estimating total polyphenols using near infrared spectroscopy. Journal of Food Science and Technology, 2018; 55: 4867–4876.

[7] Chen Q S, Chen M, Liu Y, Wu J Z, Wang X Y, Ouyang Q, et al. Application of FT-NIR spectroscopy for simultaneous estimation of taste quality and taste-related compounds content of black tea. Journal of Food Science and Technology, 2018; 55: 4363–4368.

[8] Dong C W, Zhu H K, Zhao J W, Jiang Y W, Yuan H B, Chen Q S. Sensory quality evaluation for appearance of needle-shaped green tea based on computer vision and nonlinear tools. Journal of Zhejiang University-SIENCE B, 2017; 18: 544–548.

[9] Zhu M Z, Wen B B, Wu H, Li J, Lin H Y, Li Q, et al. The quality control of tea by near-Infrared reflectance (NIR) spectroscopy and chemometrics. Journal of Spectroscopy, 2019; 2019: 8129648.

[10] Lin X H, Sun D W. Recent developments in vibrational spectroscopic techniques for tea quality and safety analyses. Trends in Food Science & Technology, 2020; 104: 163–176.

[11] Jayapal S K, Poruran S. Enhanced disease identification model for tea plant using deep learning. Intelligent Automation & Soft Computing, 2023; 35(1): 1261–1275.

[12] Hu G S, Min F. Using a multi-convolutional neural network to automatically identify small-sample tea leaf diseases. Sustainable Computing:Informatics and Systems, 2022; 35: 100696.

[13] Li H, Shi H T, Du A H, Mao Y L, Fan K, Wang Y, et al. Symptom recognition of disease and insect damage based on Mask R-CNN, wavelet transform, and F-RNet. Frontiers in Plant Science, 2022; 13: 922797.

[14] Karmokar B C, Ullah M S, Siddiquee M K, Alam K M R. Tea leaf diseases recognition using neural network ensemble. International Journal of Computer Applications, 2015; 114: 27–30.

[15] Yuan L, Yan P, Han W Y, Huang Y B, Wang B, Zhang J C, et al. Detection of anthracnose in tea plants based on hyperspectral imaging. Computers and Electronics in Agriculture, 2019; 167: 105039.

[16] Zhao X H, Zhang, J C, Huang Y B, Tian Y Y, Yuan L. Detection and discrimination of disease and insect stress of tea plants using hyperspectral imaging combined with wavelet analysis. Computers and Electronics in Agriculture, 2022; 193: 106717.

[17] Hu G S, Wan M Z, Wei K, Ye R H. Computer vision based method for severity estimation of tea leaf blight in natural scene images. European Journal of Agronomy, 2023; 144: 126756.

[18] Hu G S, Wu H Y, Zhang Y, Wan M Z. A low shot learning method for tea leaf's disease identification. Computers and Electronics in Agriculture, 2019; 163: 104852.

[19] Hu G S, Yang X W, Zhang Y, Wan M Z. Identification of tea leaf diseases by using an improved deep convolutional neural network. Sustainable Computing:Informatics and Systems, 2019; 24: 100353.

[20] Datta S, Gupta N. A novel approach for the detection of tea leaf disease using deep neural network. International Conference on Machine Learning and Data Engineering, 2023; 218: 2273–2286.

[21] Mukhopadhyay S, Paul M, Pal R, De D. Tea leaf disease detection using multi-objective image segmentation. Multimedia Tools and Applications, 2020; 80: 753–771.

[22] Sun Y Y, Jiang Z H, Zhang L P, Dong W, Rao Y. SLIC_SVM based leaf diseases saliency map extraction of tea plant. Computers and Electronics in Agriculture, 2019; 157: 102–109.

[23] Sun X D, Liao Y, Han X, Xie D F, Gong Z Y, Fu W, et al. Tea stalks and insect foreign bodies detection based on electromagnetic vibration feeding combination of hyperspectral imaging. Infrared Physics & Technology, 2022; 127: 104456.

[24] Sun Y B, Wang J, Cheng S M. Discrimination among tea plants either with different invasive severities or different invasive times using MOS electronic nose combined with a new feature extraction method. Computers and Electronics in Agriculture, 2017; 143: 293–301.

[25] Wang X, Huang J H, Fan W, Lu H M. Identification of green tea varieties and fast quantification of total polyphenols by near-infrared spectroscopy and ultraviolet-visible spectroscopy with chemometric algorithms. Analytical Methods, 2015; 7(2): 787–792.

[26] Wang Y J, Li L Q, Shen S S, Liu Y, Ning J M, Zhang Z Z. Rapid detection of quality index of postharvest fresh tea leaves using hyperspectral imaging. Journal of the Science of Food and Agriculture, 2020; 100(10): 3803–3811.

[27] Sun J, Zhou X, Hu Y G, Wu X H, Zhang X D, Wang P. Visualizing distribution of moisture content in tea leaves using optimization algorithms and NIR hyperspectral imaging. Computers and Electronics in Agriculture, 2019; 160: 153–159.

[28] Zhang M, Guo J M, Ma C Y, Qiu G J, Ren J J, Zeng F G, et al. An effective prediction approach for moisture content of tea leaves based on discrete wavelet transforms and bootstrap soft shrinkage algorithm. Applied Sciences, 2020; 10(14): 4839.

[29] Yamashita H, Sonobe R, Hirono Y, Morita A, Ikka T. Dissection of hyperspectral reflectance to estimate nitrogen and chlorophyll contents in tea leaves based on machine learning algorithms. Scientific Reports, 2020; 10: 17360.

[30] Wang Y J, Hu X, Jin G, Hou Z W, Ning J M, Zhang Z Z. Rapid prediction of chlorophylls and carotenoids content in tea leaves under different levels of nitrogen application based on hyperspectral imaging. Journal of the Science of Food and Agriculture, 2019; 99(4): 1997–2004.

[31] Sonobe R, Hirono Y, Oi A. Quantifying chlorophyll-*a* and *b* content in tea leaves using hyperspectral reflectance and deep learning. Remote Sensing Letters, 2020; 11(10): 933–942.

[32] Sonobe R, Sano T, Horie H. Using spectral reflectance to estimate leaf chlorophyll content of tea with shading treatments. Biosystem Engineering, 2018; 175: 168–182.

[33] Wang Y J, Hu X, Hou Z W, Ning J M, Zhang Z Z. Discrimination of nitrogen fertilizer levels of tea plant (*Camellia sinensis*) based on hyperspectral imaging. Journal of the Science of Food and Agriculture, 2018; 98(12): 4659–4664.

[34] Wang Y-J, Li T-H, Jin G, Wei Y-M, Li L-Q, Kalkhajeh Y K, et al. Qualitative and quantitative diagnosis of nitrogen nutrition of tea plants under field condition using hyperspectral imaging coupled with chemometrics. Journal of the Science of Food and Agriculture, 2020; 100(1): 161–167.

[35] Wang Y J, Jin G, Li L Q, Liu Y, Kalkhajeh Y K, Ning J M, et al. NIR hyperspectral imaging coupled with chemometrics for nondestructive assessment of phosphorus and potassium contents in tea leaves. Infrared Physics & Technology, 2020; 108: 103365.

[36] Sonobe R, Miura Y, Sano T, Horie H. Estimating leaf carotenoid contents of shade-grown tea using hyperspectral indices and PROSPECT-D inversion. International Journal of Remote Sensing, 2018; 39(5): 1306–1320.

[37] Zhang Y Y, Gao W J, Cui C J, Zhang Z Z, He L L, Zheng J K, et al. Development of a method to evaluate the tenderness of fresh tea leaves based on rapid, *in-situ* Raman spectroscopy scanning for carotenoids. Food Chemistry, 2020; 308: 125648.

[38] Luo W, Tian P, Fan G Z, Dong W T, Zhang H L, Liu X M. Non-destructive determination of four tea polyphenols in fresh tea using visible and near-infrared spectroscopy. Infrared Physics & Technology, 2022; 123: 104037.

[39] Huang Y F, Dong W T, Sanaeifar A, Wang X M, Luo W, Zhan B S, et al. Development of simple identification models for four main catechins and caffeine in fresh green tea leaf based on visible and near-infrared spectroscopy. Computers and Electronics in Agriculture, 2020; 173: 105388.

[40] Guo J M, Huang H, He X L, Cai J W, Zeng Z X, Ma C Y, et al. Improving the detection accuracy of the nitrogen content of fresh tea leaves by combining FT-NIR with moisture removal method. Food Chemistry, 2023; 405: 134905.

[41] Xu Y Q, Liu P P, Shi J, Gao Y, Wang Q-S, Yin J-F. Quality development and main chemical components of *Tieguanyin* oolong teas processed from different parts of fresh shoots. Food Chemistry, 2018; 249: 176–183.

[42] Ye N S. A minireview of analytical methods for the geographical origin analysis of teas (*Camellia sinensis*). Critical Reviews in Food Science and Nutrition, 2012; 52(9): 775–780.

[43] Tang Z, Su Y C, Er M J, Qi F; Zhang L, Zhou J Y. A local binary pattern based texture descriptors for classification of tea leaves. Neurocomputing, 2015; 168: 1011–1023.

[44] Li C L, Zong B Z, Guo H W, Luo Z, He P M, Gong S Y, et al. Discrimination of white teas produced from fresh leaves with different maturity by near-infrared spectroscopy. Spectrochim Acta Part A:Molecular and Biomolecular Spectroscopy, 2020; 227: 117697.

[45] Cai J X, Wang Y F, Xi X G, Li H, Wei X L. Using FTIR spectra and pattern recognition for discrimination of tea varieties. International Journal of Biological Macromolecules, 2015; 78: 439–446.

[46] Zilvan V, Ramdan A, Heryana A, Krisnandi D, Suryawati E, Yuwana R S, et al. Convolutional variational autoencoder-based feature learning for automatic tea clone recognition. Journal of King Saud University - Computer and Information Sciences, 2022; 34(6, PartB): 3332–3342.

[47] Dutta D, Kumar Das P, Bhunia U K, Singh U, Singh S, Sharma J R, et al. Retrieval of tea polyphenol at leaf level using spectral transformation and multi-variate statistical approach. International Journal of Applied Earth Observation and Geoinformation, 2015; 36: 22–29.

[48] Esteki M, Memarbashi N, Simal-Gandara J. Classification and authentication of tea according to their harvest season based on FT-IR fingerprinting using pattern recognition methods. Journal of Food Composition and Analysis, 2023; 115: 104995.

[49] Chen C L, Lu J Z, Zhou M C, Yi J, Liao M, Gao Z M. A YOLOv3-based computer vision system for identification of tea buds and the picking point. Computers and Electronics in Agriculture, 2022; 198: 107116.

[50] Zhang Y G, Ye X S, Zhang X W, Huang W, Zhao H. Natural variations and dynamic changes of nitrogen indices throughout growing seasons for twenty tea plant (*Camellia sinensis*) varieties. Plants, 2020; 9(10): 1333.

[51] Yang P D, Liu Z, Zhao Y, Cheng Y, Li J, Ning J, et al. Comparative study of vegetative and reproductive growth of different tea varieties response to different fluoride concentrations stress. Plant Physiology and Biochemistry, 2020; 154: 419–428.

[52] Kubo N, Mimura Y, Matsuda T, Nagano A J, Hirai N, Higashimoto S, et al. Classification of tea (*Camellia sinensis*) landraces and cultivars in Kyoto, Japan and other regions, based on simple sequence repeat markers and restriction site-associated DNA sequencing analysis. Genetic Resources and Crop Evolution, 2019; 66: 441–451.

[53] Nidamanuri R R. Hyperspectral discrimination of tea plant varieties using machine learning, and spectral matching methods. Remote Sensing Applications:Society and Environment, 2020; 19: 100350.

[54] Cao Q, Yang G J, Wang F, Chen L Y, Xu B, Zhao C J, et al. Discrimination of tea plant variety using in-situ multispectral imaging system and multi-feature analysis. Computers and Electronics in Agriculture, 2022; 202: 107360.

[55] Tu Y X, Bian M, Wan Y K, Fei T. Tea cultivar classification and biochemical parameter estimation from hyperspectral imagery obtained by UAV. PeerJ, 2018; 6: e4858.

[56] Zhong Y Q, Kang Z L, Wang P, Luo X. A method of distinguishing tea varieties based on hyperspectral imaging. Journal of Physics:Conference Series, 2020; 1617: 012061.

[57] Zhou J, Cheng H, Zeng J M, Wang L Y, Wei K, He W, et al. Study on identification and traceability of tea material cultivar by combined analysis of multi-partial least squares models based on near infrared spectroscopy. Spectroscopy and Spectral Analysis, 2010; 30: 2650–2653.

[58] Li X L, He Y. Discriminating varieties of tea plant based on Vis/NIR spectral characteristics and using artificial neural networks. Biosystems Engineering, 2008; 99(3): 313–321.

[59] Tan S M, Luo R M, Zhou Y P, Xu H, Song D D, Ze T, et al. Boosting partial least-squares discriminant analysis with application to near infrared spectroscopic tea variety discrimination. Journal of Chemometrics, 2012; 26(1-2): 34–39.

[60] Zhang L, Zou L, Wu C Y, Jia J M, Chen J N. Method of famous tea sprout identification and segmentation based on improved watershed algorithm. Computers and Electronics in Agriculture, 2021; 184: 106108.

[61] Qian C H, Li M Y, Ren Y. Tea sprouts segmentation via improved deep convolutional encoder-decoder network. IEICE Transactions on Information and Systems, 2020; E103.D(2): 476–479.

[62] Chen Y T, Chen S F. Localizing plucking points of tea leaves using deep convolutional neural networks. Computers and Electronics in Agriculture, 2020; 171: 105298.

[63] Xu W K, Zhao L G, Li J, Shang S Q, Ding X P, Wang T W. Detection and classification of tea buds based on deep learning. Computers and Electronics in Agriculture, 2022; 192: 106547.

[64] Yang H L, Chen L, Ma Z B, Chen M T, Zhong Y, Deng F, et al. Computer vision-based high-quality tea automatic plucking robot using Delta parallel manipulator. Computers and Electronics in Agriculture, 2021; 181: 105946.

[65] Zhang L, Zhang H D, Chen Y D, Dai S H, Li X M, Kenji I, et al. Real-

time monitoring of optimum timing for harvesting fresh tea leaves based on machine vision. Int J Agric & Biol Eng, 2019; 12(1): 6–9.
[66] Yan L J, Wu K H, Lin J, Xu X G, Zhang J C, Zhao X Z, et al. Identification and picking point positioning of tender tea shoots based on MR3P-TS model. Front. Plant Sci., 2022; 13: 962391.
[67] Hu G S, Li S Q, Wan M Z, Bao W X. Semantic segmentation of tea geometrid in natural scene images using discriminative pyramid network. Applied Soft Computing, 2021; 113: 107984.
[68] Yang H L, Chen L, Chen M T, Ma Z B, Deng F, Li M Z, et al. Tender tea shoots recognition and positioning for picking robot using improved YOLO-V3 model. IEEE Access, 2019; 7: 180998–181011.
[69] Li Y T, He L Y, Jia J M, Lv J, Chen J N, Qiao X, et al. In-field tea shoot detection and 3D localization using an RGB-D camera. Computers and Electronics in Agriculture, 2021; 185: 106149.
[70] Chen B, Yan J L. Fresh tea shoot maturity estimation via multispectral imaging and deep label distribution learning. IEICE Transactions on Information and Systems, 2020; E103.D: 2019–2022,
[71] Wang T, Zhang K M, Zhang W, Wang R Q, Wan S M, Rao Y, et al. Tea picking point detection and location based on Mask-RCNN. Information Processing in Agriculture, 2021; 10(2): 267–275.
[72] Asante E A, Du Z, Lu Y Z, Hu Y G. Detection and assessment of nitrogen effect on cold tolerance for tea by hyperspectral reflectance with PLSR, PCR, and LM models. Information Processing in Agriculture, 2021; 8(1): 96–104.
[73] Kumar A, Manjunath K R, Meenakshi, Bala R, Sud R K, Singh R D, et al. Field hyperspectral data analysis for discriminating spectral behavior of tea plantations under various management practices. International Journal of Applied Earth Observation and Geoinformation, 2013; 23: 352–359.
[74] Kang Y S, Ryu C, Suguri M, Park S B, Kishino S, Onoyama H. Estimating the catechin concentrations of new shoots in green tea fields using ground-based hyperspectral imagery. Food Chemistry, 2022; 370: 130987.
[75] Cui L H, Yan L J, Zhao X H, Yuan L, Jin J, Zhang J C. Detection and discrimination of tea plant stresses based on hyperspectral imaging technique at a canopy level. Phyton-International Journal of Experimental Botny, 2021; 90(2): 621–634.
[76] Chen L Y, Xu B, Zhao C J, Duan D D, Cao Q, Wang F. Application of multispectral camera in monitoring the quality parameters of fresh tea leaves. Remote Sensing, 2021; 13(18): 3719.
[77] Wang Y J, Jin S S, Li M H, Liu Y, Li L Q, Ning J M, et al. Onsite nutritional diagnosis of tea plants using micro near-infrared spectrometer coupled with chemometrics. Computers and Electronics in Agriculture, 2020; 175: 105538.
[78] Cao Q, Yang G J, Duan D D, Chen L Y, Wang F, Xu B, et al. Combining multispectral and hyperspectral data to estimate nitrogen status of tea plants (*Camellia sinensis* (L) O. Kuntze) under field conditions. Computers and Electronics in Agriculture, 2022; 198: 107084.
[79] Luo D N, Gao Y, Wang Y, Shi Y J, Chen S Z, Ding, Z T, et al. Using UAV image data to monitor the effects of different nitrogen application rates on tea quality. Journal of Science of Food and Agriculture, 2022; 102(4): 1540–1549.
[80] Xu J, Guga S R, Rong G Z, Riao D, Liu X P, Li K W, et al. Estimation of frost hazard for tea tree in Zhejiang province based on machine learning. Agriculture, 2021; 11(7): 607.
[81] Chen P P, Li C J, Chen S L, Li Z Y, Zhang H Y, Zhao C J. Tea cultivation suitability evaluation and driving force analysis based on AHP and geodetector results: A case study of Yingde in Guangdong, China. Remote Sensing, 2022; 14(10): 2412.
[82] Xiong Y, Kang Q W, Xu W H, Huang S D, Dai F, Wang L G, et al. The dynamics of tea plantation encroachment into forests and effect on forest landscape pattern during 1991-2021 through time series Landsat images. Ecological Indicators, 2022; 141: 109132.
[83] Li N, Zhang D, Li L W, Zhang Y L. Mapping the spatial distribution of tea plantations using high-spatiotemporal-resolution imagery in northern Zhejiang, China. Forests, 2019; 10(10): 856.
[84] Huang X, Zhu Z R, Li Y S, Wu B, Yang M. Tea garden detection from high-resolution imagery using a scene-based framework. Photogramm Engineering & Remote Sensing, 2018; 84(11): 723–731.
[85] Dihkan M, Guneroglu N, Karsli F, Guneroglu A. Remote sensing of tea plantations using an SVM classifier and pattern-based accuracy assessment technique. International Journal of Remote Sensing, 2013; 34(23): 8549–8565.
[86] Akar Ö, Güngör O. Integrating multiple texture methods and NDVI to the Random Forest classification algorithm to detect tea and hazelnut plantation areas in northeast Turkey. International Journal of Remote Sensing, 2015; 36(2): 442–464.
[87] Wang B, Li J, Jin X F, Xiao H. Mapping tea plantations from multi-seasonal Landsat-8 OLI imageries using a random forest classifier. Journal of the Indian Society of Remote Sensing, 2019; 47: 1315–1329.
[88] Xu W H, Qin Y W, Xiao X M, Di G Z, Doughty R B, Zhou Y T, et al. Quantifying spatial-temporal changes of tea plantations in complex landscapes through integrative analyses of optical and microwave imagery. International Journal of Applied Earth Observation and Geoinformation, 2018; 73: 697–711.
[89] Chen Y J, Tian S F. Comparison of pixel- and object-based image analysis for tea plantation mapping using hyperspectral Gaofen-5 and synthetic aperture radar data. Journal of Applied Remote Sensing, 2020; 14(4): 044516.
[90] Chu H J, Wang C K, Kong S J, Chen K C. Integration of full-waveform LiDAR and hyperspectral data to enhance tea and areca classification. GIScience & Remote Sensing, 2016; 53(4): 542–559.
[91] Xu W H, Huang S D, Wu C, Xiong Y, Wang L G, Lu N, Kou W L. The pruning phenological phase-based method for extracting tea plantations by field hyperspectral data and Landsat time series imagery. Geocarto International, 2022; 37(7): 2116–2136.
[92] Kotikot S M, Flores A, Griffin R E, Sedah A, Nyaga J, Mugo R, et al. Mapping threats to agriculture in East Africa: Performance of MODIS derived LST for frost identification in Kenya's tea plantations. Internatioanl Journal of Applied Earth Observation and Geoinformation, 2018; 72: 131–139.
[93] Zhu J, Pan Z W, Wang H, Huang P J, Sun J L, Qin F, Liu Z Z. An improved multi-temporal and multi-feature tea plantation identification method using Sentinel-2 imagery. Sensors, 2019; 19(9): 2087.
[94] Zitová B, Flusser J. Image registration methods: A survey. Image and Vision Computing, 2003; 21(11): 977–1000.
[95] Chen Y J, Tian S F. Feature-level fusion between Gaofen-5 and Sentinel-1A data for tea plantation mapping. Forests, 2020; 11(12): 1357.
[96] Tang Z X, Li M M, Wang X Q. Mapping tea plantations from VHR images using OBIA and convolutional neural networks. Remote Sensing, 2020; 12(18): 2935.
[97] Huang S D, Xu W H, Xiong Y, Wu C, Dai F, Xu H F, et al. Combining textures and spatial features to extract tea plantations based on object-oriented method by using multispectral image. Spectroscopy and Spectral Analysis, 2021; 41(8): 2565–2571.
[98] Jayasinghe S L, Kumar L. Potential impact of the current and future climate on the yield, quality, and climate suitability for tea [*Camellia sinensis* (L.) O. Kuntze]: A systematic review. Agronomy, 2021; 11(4): 619.
[99] Jayasinghe S L, Kumar L, Hasan M K. Relationship between environmental covariates and Ceylon tea cultivation in Sri Lanka. Agronomy, 2020; 10(4): 476.
[100] Li B, Zhang F, Zhang L-W, Huang J-F, Jin Z-F, Gupta D K. Comprehensive suitability evaluation of tea crops using GIS and a modified land ecological suitability evaluation model. Pedosphere, 2012; 22(1): 122–130.
[101] Das A C, Noguchi R, Ahamed T. Integrating an expert system, GIS, and satellite remote sensing to evaluate land suitability for sustainable tea production in Bangladesh. Remote Sensing, 2020; 12(24): 4136.
[102] Jayasinghe S L, Kumar L. Climate change may imperil tea production in the four major tea producers according to climate prediction models. Agronomy, 2020; 10(10): 1536.
[103] Xing W W, Zhou C, Li J L, Wang W Y, He J C, Tu Y J, et al. Suitability evaluation of tea cultivation using machine learning technique at town and village scales. Agronomy, 2022; 12(9): 2010.
[104] Zhang S Q, Liu W D, Cheng X M, Wang Z Z, Yuan F J, Wu W G, et al. Evaluating the productivity of ancient Pu'er tea trees (*Camellia sinensis* var. assamica): A multivariate modeling approach. Plant Methods, 2022; 18: 95.
[105] Lou W P, Sun K, Zhao Y M, Deng S R, Zhou Z D. Impact of climate change on inter-annual variation in tea plant output in Zhejiang, China. International Journal of Climatology, 2021; 41(S1): E479–E490.
[106] Kimura K, Yasutake D, Nakazono K, Kitano M. Dynamic distribution of thermal effects of an oscillating frost protective fan in a tea field. Biosystems Engineering, 2017; 164: 98–109.

[107] Kimura K, Yasutake D, Oki T, Yoshida K, Kitano M. Dynamic modelling of cold-hardiness in tea buds by imitating past temperature memory. Annals of Botany, 2021; 127(3): 317–326.

[108] Kimura, K, Kudo K, Maruyama A. Spatiotemporal distribution of the potential risk of frost damage in tea fields from 1981-2020: A modeling approach considering phenology and meteorology. Journal of Agricultural Meteorology, 2021; 77(4): 224–234.

[109] Kotikot S M, Flores A, Griffin R E, Nyaga J, Case J L, Mugo R, et al. Statistical characterization of frost zones: Case of tea freeze damage in the Kenyan highlands. International Journal of Applied Earth Observation and Groinformation, 2020; 84: 101971.

[110] Wu Z Y, Li K Q, Yuan L, Zhang J C, Zhou X F, Chen D M, et al. Tea plantation frost damage early warning using a two-fold method for temperature prediction. Phyton-International Journal of Experimental Botany, 2022; 91(10): 2269–2282.

[111] Wang P J, Ma Y P, Tang J X, Wu D R, Chen H, Jin Z F, et al. Spring frost damage to tea plants can be identified with daily minimum air temperatures estimated by MODIS land surface temperature products. Remote Sensing, 2021; 13(6): 1177.

[112] Wang P J, Tang J X, Ma Y P, Wu D R, Yang J Y, Jin Z F, et al. Mapping threats of spring frost damage to tea plants using satellite-based minimum temperature estimation in China. Remote Sensing, 2021; 13(14): 2713.

[113] Saha J K, Mehedi Adnan K M, Sarker S A. Analysis of growth trends in area, production and yield of tea in Bangladesh. Journal of Agriculture and Food Research, 2021; 4: 100136.

[114] Fauziana F, Danoedoro P, Heru Murti S. Linear spectral mixture analysis of SPOT-7 for tea yield estimation in Pagilaran Estate, Batang Central Java. IOP Conference Series:Earth and Environmental Science, 2016; 47: 012034.

[115] Phan P, Chen N C, Xu L, Chen Z Q. Using multi-temporal MODIS NDVI data to monitor tea status and forecast yield: A case study at Tanuyen, Laichau, Vietnam. Remote Sensing, 2020; 12(11): 1814.

[116] Janifer Jabin Jui S, Masrur Ahmed A A, Bose A, Raj N, Sharma E, Soar J, et al. Spatiotemporal hybrid random forest model for tea yield prediction using satellite-derived variables. Remote Sensing, 2022; 14((3): 805.

[117] Rao N R, Kapoor M, Sharma N, Venkateswarlu K. Yield prediction and waterlogging assessment for tea plantation land using satellite image-based techniques. International Journal of Remote Sensing, 2007; 28(7): 1561–1576.

[118] Ramadanningrum D P, Kamal M, Murti S H. Image-based tea yield estimation using Landsat-8 OLI and Sentinel-2B images. Remote Sensing Applications:Society and Environment, 2020; 20: 100424.

[119] Batool D, Shahbaz M, Asif H S, Shaukat K, Alam T M, Hameed I A, et al. A hybrid approach to tea crop yield prediction using simulation models and machine learning. Plants, 2022; 11(15): 1925.

[120] Nitin K, Tripathi S S, Honda K. Tea yield modeling based on satellite derived LAI. Geocarto International, 2004; 19(3): 51–54.

[121] Chen X, Wang D H, Li J, Xu T T, Lai K Q, Ding Q, et al. A spectroscopic approach to detect and quantify phosmet residues in Oolong tea by surface-enhanced Raman scattering and silver nanoparticle substrate. Food Chemistry, 2020; 312: 126016.

[122] Zhu J J, Sharma A S, Xu J, Xu Y, Jiao T H, Ouyang Q, et al. Rapid on-site identification of pesticide residues in tea by one-dimensional convolutional neural network coupled with surface-enhanced Raman scattering. Spectrochim Acta Part A:Molecular and Biomolecular Spectroscopy, 2021; 246: 118994.