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REVIEW PAPER TOPIC - SMART SENSING FOR NON-DESTRUCTIVE FRUIT AND VEGETABLE ASSESSMENT: A COMPREHENSIVE REVIEW OF NIR SPECTROSCOPY, MACHINE VISION AND YIELD-QUALITY PREDICTION UNDER A CHANGING CLIMATE

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ABSTRACT
Rapid, non-destructive, quantitative evaluation of quality and yield of fresh produce has become a core activity in horticultural production, postharvest handling, and supply-chain management. This is increasingly important as climate variability weakens the relationships between external appearance, internal content, and final performance of produce each year. This review compiles the present knowledge on smart sensing technologies for fruits and vegetables, focusing on near-infrared (NIR) and visible/NIR spectroscopy, hyper-spectral and multi-spectral imaging, machine vision coupled with deep-learning-based grading, and other related technologies including electronic nose, fluorescence imaging, X-ray computed tomography and acoustic sensing. It also reviews the remotely and proximally sensed instruments for estimating yields, including UAVs, satellite vegetation indices, wireless sensor networks, and the Internet of Things. The discussion delves to some extent into the physics, instrumentation and chemometric or machine-learning pipelines preprocessing, wavelength selection, partial least squares regression, support vector machines, random forests, and convolution neural network architectures (e.g., YOLO, Mask R-CNN) all turning raw spectral, image or sensor data into quantitative predictions of soluble solids content, titratable acidity, firmness, dry matter, pigmentation, internal disorders and fruit count. Case studies of apple, grape, citrus, mango, blueberry, tomato, potato and many other important crops are compared to demonstrate the current level of maturity and the limitations of each technology. Ambient temperature, high CO_2, drought and UV/ozone stress modify biochemical composition of the fruit and canopy reflectance, so we focus on the influence of these changing environmental factors on sensor calibration stability, model transferability and the potential to predict yield quality reliability. Corresponding methodologies to keep the prediction performance stable under changing climatic baselines calibration transfer, domain adaptation and multi-sensor data fusion are reviewed as well. The review ends by describing the challenges that still need to be: transfer of calibration models between cultivars, seasons and instruments; cost and computational complexity of hyper- spectral and deep-learning pipelines; and lack of standardised climate- resilient validation protocols. It concludes by suggesting avenues for running smart sensing in precision horticulture, climate-adaptive breeding and supply-chain decision-making.

KEYWORDS: near-infrared spectroscopy; hyperspectral imaging; machine vision; non-destructive quality assessment; deep learning; yield prediction; precision agriculture; remote sensing; climate change; postharvest technology

1. INTRODUCTION
Fruits and vegetables are highly perishable and biologically variable, and their value depends both on their external appearance, including size, shape, colour, and absence of defects, and on their internal composition, such

as the content of soluble solids, titratable acidity, firmness, dry matter, pigmentation and nutrient density. Traditional methods for quality evaluation involve destructive laboratory analysis or subjective human grading, both of which are time consuming, require considerable amounts of labor and are inadequate to match the demands of modern fruit-packing houses and supply chain (Nicolai *et al*., 2007; Abasi *et al*., 2018). However, during approximately past three decades, certain non-destructive smart sensing technologies have progressed from the laboratory to commercial applications. Vis/NIR spectroscopy, hyperspectral and multispectral imaging, machine vision, electronic nose, fluorescence imaging, X-ray computed tomography and acoustic sensing can be found in both in-line grading systems and portable field instruments (Nicolai *et al*., 2014; Lorente *et al*., 2012; Gao *et al*., 2010; Wang *et al*., 2015).

Remote and proximal sensing platforms have been widely used in precision agriculture to monitor crop conditions and predict yield at field and orchard scale. UAVs, satellite-based vegetation indices and wireless sensor networks (WSNs) integrated in Internet-of-Things (IoT) architectures now perform most of these tasks (Mulla, 2013; Ojha *et al*., 2015; Weiss *et al*., 2020). These sensing techniques, when combined with machine learning and, more recently, deep learning, have significantly improved the accuracy, throughput, and level of automation that can be achieved in both quality grading and yield prediction. Nowadays, convolutional neural network architectures such as YOLO and Mask R-CNN are standard approaches for fruit detection, counting and defect classification (LeCun *et al*., 2015; He *et al*., 2016, 2017; Kamilaris and Prenafeta-Boldu, 2018).

There is also increasing evidence that the climate variability itself is changing the problem. Increased average and extreme temperatures, high atmospheric CO_2 concentrations, changes in precipitation and drought regimes, and higher levels of UV and tropospheric ozone have been found to significantly influence fruit and vegetable biochemical composition, canopy reflectance and postharvest physiology (Moretti *et al*., 2010; Bisbis *et al*., 2018; Booker *et al*., 2009). This raises a little-studied challenge for smart sensing: calibration models developed from spectral or imaging data under one set of environmental and seasonal conditions tend to loses predictive power when applied to samples grown or measured under different environmental regimes. This is essentially the model-drift and calibration-transfer problem that chemometricians have struggled with for some time, now playing out across a changing climate (Cortes *et al*., 2019; Zou *et al*., 2010).

The aim of this review is to give a comprehensive, technology-by-technology account of smart sensing and non-destructive assessment for fruits and vegetables. Sections 2 through 4 cover the physical principles and instrumentation behind Vis/NIR spectroscopy, hyperspectral and multispectral imaging, and complementary sensing approaches, along with the chemometric and machine-learning/deep-learning pipelines used to convert sensor output into quality predictions, and machine-vision-based grading and robotic harvesting systems. Section 5 turns to remote-sensing and IoT-based approaches for yield estimation. Section 6 is where this review departs most from earlier surveys: it looks specifically at the evidence for how sensing accuracy and yield-quality prediction reliability hold up as environmental and climatic conditions shift.

2. Near-Infrared and Visible/NIR Spectroscopy

Near-infrared (NIR) radiation with approximate wavelength of 780-2500 nm, is absorbed by overtone or combination vibrational modes of C-H, O-H and N-H bonds within organic compounds. As a consequence, the absorbance spectrum contains information about the sugars, water, acids, and other biochemical components of the fruit and vegetable tissue (Lin and Ying, 2009; Nicolai *et al*., 2007). In simple terms, a Vis/NIR system requires three basic components: a light source (traditionally halogen, though LED arrays are becoming more prevalent), a method of delivering the sample in reflectance, transmittance, or interactance mode and a spectrometer (diode-array, InGaAs or CCD-based) to capture the wavelength-resolved signal. Chemometric modelling then converts that captured signal into a quantitative prediction (Figure 1).

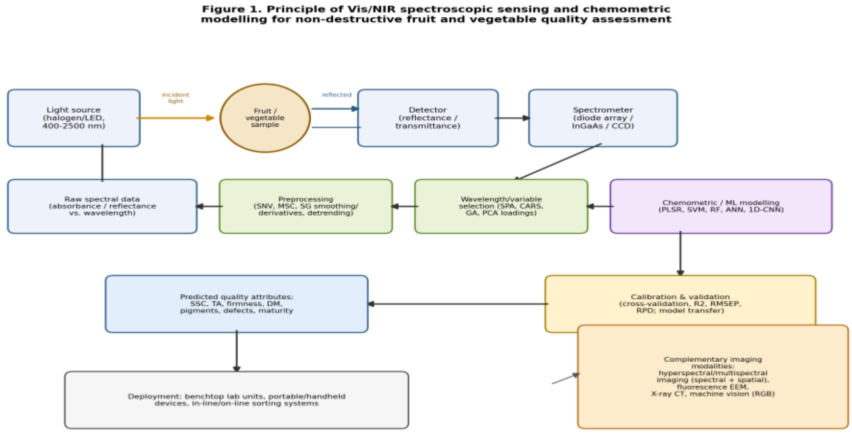

Figure 1. Vis/NIR spectroscopic sensing and chemometric modelling for non-destructive fruit and vegetable quality assessment: the sequence from light-sample interaction through preprocessing, variable selection, model calibration and field deployment. (Original figure; conceptual framework drawn from Nicolai *et al.*, 2007; Lin and Ying, 2009; Barnes *et al.*, 1989)

2.1 Chemometric Preprocessing and Calibration
Raw spectra are seldom directly usable as they are obtained, due to the presence of scatter, path-length variation and instrumental noise. Common preprocessing steps- standard normal variate (SNV) transformation, multiplicative scatter correction (MSC), Savitzky-Golay smoothing, derivatives and detrending are used prior to calibration (Barnes *et al*., 1989; Naes *et al*., 2002). The dimensionality is then typically reduced using wavelength or variable selection techniques such as the successive projections algorithm (SPA), competitive adaptive reweighted sampling (CARS), genetic algorithms, and principal component loadings analysis; this also tends to make the final models more robust and easier to interpret (Zou *et al*., 2010). Partial least squares regression (PLSR) is still the workhorse calibration technique for relating preprocessed spectra to reference quality values, primarily because it is reasonably effective at handling collinear, high-dimensional spectral data (Cheng and Sun, 2015; Cozzolino *et al*., 2011). However, support vector machines, random forest, artificial neural networks, and one-dimensional convolutional neural networks are now commonly tested against PLSR for both regression and classification alike.
2.2 Applications to Internal Quality Attributes
Soluble solids content (SSC) is where Vis/NIR spectroscopy has been most successful: for various fruits typical coefficients of determination (R2) of 0.70-0.95 are reported, with prediction errors of 0.5-1.0 degrees Brix (Saranwong *et al*., 2004; Schmilovitch *et al*., 2000; Alamar *et al*., 2007). Firmness and titratable acidity are more challenging objectives, with R2 values tending to be in the range of 0.4 to 0.8. This discrepancy probably illustrates the less direct nature of these physical or biochemical characteristics when compared with the chemical bonds that NIR directly investigates (Peng and Lu, 2008; Nicolai *et al*., 2014). Dry matter content a key measure of maturity and eating quality of avocado, kiwifruit and mango has been predicted accurately using portable field NIR instruments (Subedi and Walsh, 2020; Schaare and Fraser, 2000). Considerable coverage of citrus internal quality (SSC, acidity, juice fraction) has been given, with commercial NIR-based grading of citrus already taking place in a number of countries (Magwaza *et al*., 2012). Vis/NIR spectroscopy has also been found suitable for other chemical quality parameters in vegetable crops like onion (Sans *et al*., 2018), and more generally for sorting fruits and vegetables based on soluble solids and dry matter content (Walsh *et al*., 2004).
2.3 Portable and Handheld Vis/NIR Devices
A parallel line of investigation has focused on miniature, low-cost, LED-based Vis/NIR devices that growers themselves could use while on the field to make harvest timing decisions. For example, Beghi and colleagues developed a portable Vis/NIR system for assessing nutraceutical properties of apples and ripeness indices for blueberries and quality parameters for grapes, they tested such systems in the vineyard and orchard rather than successfully in a laboratory (Beghi *et al*., 2013a, 2013b). Simplified four-wavelength broadband LED-based systems have also proven to approach the accuracy of full-spectrum benchtop spectrophotometer for estimation of ripeness of grapes and general fruit/vegetable at much lower prices (Giovenzana *et al*., 2014, 2015; Civelli *et al*., 2015). Electronic-nose and Vis/NIR combinations have also been reviewed as on-field instrumentation for freshness and ripeness monitoring along the postharvest chain (Beghi *et al*., 2017).

Table 1. Vis/NIR spectroscopy applications and reported prediction performance for internal quality attributes, across major fruit and vegetable crops.

Crop	Target attribute(s)	Typical performance (R2 range)	Representative reference
Apple	SSC, firmness, acidity phenolics	R2 = 0.44–0.86 (attribute-dependent)	Beghi *et al*., 2013b; Alamar *et al*., 2007
Mango	Ripe-stage eating quality, dry matter	R2 = 0.70–0.90	Saranwong *et al*., 2004 Cortes *et al*., 2017
Citrus	SSC, acidity, juice content	R2 = 0.75–0.92	Magwaza *et al*., 2012 Schmilovitch *et al*., 2000
Grape	SSC, ripeness index phytosanitary status	R2/accuracy = 0.80–0.94	Giovenzana *et al*., 2014; Ye *et al*., 2023
Blueberry	Ripeness index, bruise detection	R2 = 0.70 (bruise, 30 min post-impact)	Beghi *et al*., 2013a Pandiselvam *et al*., 2022
Kiwifruit	SSC, dry matter, internal properties	R2 = 0.80–0.90	Schaare and Fraser, 2000
Avocado	Dry matter content	R2 > 0.85 with portable NIR	Subedi and Walsh, 2020
Tomato/vegetables	SSC, quality control (mass distribution)	R2 = 0.65–0.85	Beghi *et al*., 2018

3. Hyperspectral and Multispectral Imaging
Hyperspectral imaging (HSI) combines the principles of spectroscopy and imaging: at each pixel a full spectrum is acquired, resulting in a spectral cube that reveals the chemical and spatial heterogeneity of the fruit and vegetable tissue, which cannot be achieved by point-based spectroscopy (Lorente *et al*., 2012; ElMasry *et al*., 2012; Chandrasekaran *et al*., 2019). Multispectral imaging makes a different trade-off by only acquiring a few preselected wavebands. It compromises spectral resolution for speed and cost effectiveness, which is the reason

behind its popularization in on-line real-time defect detection on the grading lines (Feng *et al*., 2018; Sanchez *et al*., 2020). Early on, the identification of an effective set of wavebands was recognized as being key to making such systems work (Kleynen *et al*., 2003).

3.1 Internal Quality and Maturity Assessment

Hyperspectral scattering imaging has been applied for determination of firmness and soluble solid content (SSC) of peach and apple based on the light penetration depth in fruit tissue at different wavelengths (Lu and Peng, 2006; Peng and Lu, 2008), and multispectral scattering methods have been also used for discrimination of firmness and maturity of pome fruit (Pu *et al*., 2015). When combined with deep learning, the reviews indicate internal-quality regression tasks (SSC, firmness, moisture) often report R2 values within 0.65-0.92, while external defect and safety classification tasks result in substantially higher performance (often reaching 95% or more) (Zou *et al*., 2025; Huang *et al*., 2014). Hyperspectral imaging also has been used to monitor moisture during processing potato slices in hot-air drying (Amjad *et al*., 2018) and green pepper (Faqeerzada *et al*., 2020) being two instances.

3.2 External Defect and Safety Inspection

Slight external imperfections bruising, chilling damage, mold contamination, pesticide residue are all that hyperspectral and multispectral imaging is particularly good at detecting, due to the relevant spectral signature being not in the visible range, and therefore not detectable by conventional RGB cameras. The technical basis for this was established by a series of early investigations: bruise detection in Golden Delicious apples using multiple NIR wavebands (Xing *et al*., 2005); multispectral reflectance combined with fluorescence imaging for apple defects (Ariana *et al*., 2006a); NIR hyperspectral reflectance imaging for bruise detection in pickling cucumbers (Ariana *et al*., 2006b); genetic-artificial-neural-network-based spectral imaging for cherry defects (Guyer and Yang, 2000); general surface defect and contaminant detection (Mehl *et al*., 2004); and classification of citrus skin blemishes based on multispectral information and morphological attributes (Blasco *et al*., 2009). More recent deep-learning-fused systems have considerably improved on this with reports of classification accuracies within 90-99% for detecting bruising, defect and pesticide-residue in banana, mango, avocado and grape (Ye *et al*., 2023; Zou *et al*., 2025). Machine learning classification of geometric and morphological features in images was also applied to cultivar identification, for example in identifying sour cherry pits (Ropelewska *et al*., 2021).

3.3 Fluorescence Imaging

Chlorophyll, phenolics, and other endogenous fluorophores produce native fluorescence under UV or blue excitation, fluorescence imaging takes advantage of this feature as a more cost-effective and non-contact method compared to full hyperspectral systems for estimation of chlorophyll, assessment of ripeness and defects (Huang *et al*., 2024). Excitation-emission matrix (EEM) fluorescence techniques have been used for sweet pepper cultivar identification (Huang *et al*., 2022), classification of citrus peel based on excitation-wavelength-optimized fluorescence emission (Momin *et al*., 2012), and detection of defects in cherry tomato and monitoring freshness of apple by LED-induced fluorescence spectroscopy (Gao *et al*., 2016; Zhang *et al*., 2012; Karoui and Blecker, 2011). Combining fluorescence imaging and machine learning also enabled the identification of mechanical damage in green bell pepper (Fatchurrahman *et al*., 2024).

3.4 Electronic Nose, X-ray CT and Acoustic Sensing

The volatile organic compounds released during ripening of fruit are profiled by electronic-nose (e-nose) instruments employing arrays of gas sensors, providing a non-optical physicochemical method for ripeness/quality grading (Baietto and Wilson, 2015); related artificial-nose technologies have also been reviewed for early detection of plant pests (Cui *et al*., 2018). Applications reported include the classification of ripening stages using metal-oxide semiconductor sensor arrays in combination with artificial neural networks (Adak and Yumusak, 2016), portable electrochemical e-nose systems for quality evaluation of food (Wojnowski *et al*., 2017), and the identification of postharvest disease in the asymptomatic stage (Ali *et al*., 2023). X-ray computed tomography (CT), on the other hand, gives a three-dimensional image of the internal structure and has been applied in identification of internal defects (Du *et al*., 2019).

4. Machine Vision, Deep Learning and AI-Driven Data Fusion

Machine vision systems process RGB or multispectral images, either by means of classical image processing algorithms composed of underlying geometric model-fitting methods such as random sample consensus (Fischler and Bolles, 1981) or by deep convolutional neural networks (CNNs). These systems have replaced traditional technology for election-based external grading and sizing by including early machine-vision-based grading research (Blasco *et al*., 2003) that has been reviewed extensively elsewhere (Sun, 2016). Now, the same underlying approaches are increasingly guiding robotic harvesting as well (Zhang *et al*., 2014; Wu and Sun, 2013). General: The full multi-sensor, AI-enabled pipeline linking these sensing modalities to both quality and yield prediction output is schematized in Figure 2.

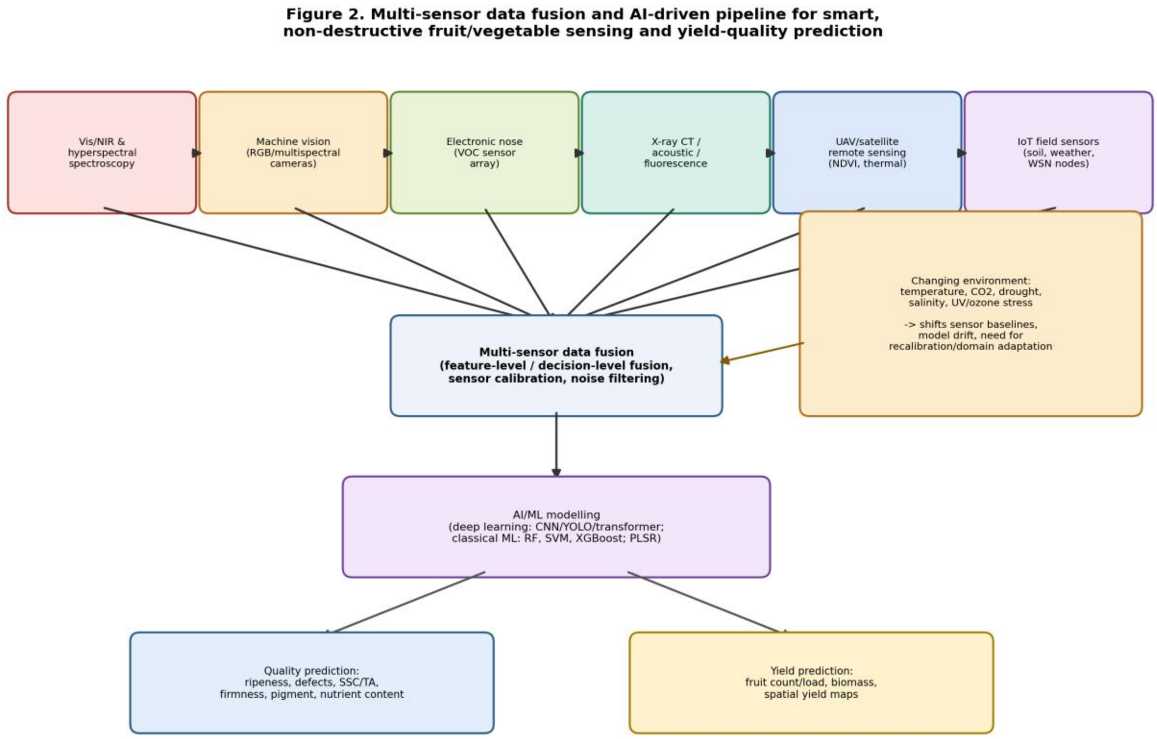

Figure 2. The smart, non-destructive fruit/vegetable sensing and yield-quality prediction based on multi-sensor data fusion and AI techniques: sensor outputs are fused, modelled and translated into quality and yield predictions, while environmental changes induce the need for model recalibration. (Original figure; conceptual framework from Kamilaris and Prenafeta-Boldu, 2018; Zhang *et al*., 2014; Wu and Sun, 2013)

4.1 CNN-Based Grading and Defect Detection

The accuracy of fruit grading has been greatly enhanced by convolutional neural network architectures compared with traditional machine-vision pipelines. A system that integrates CNN-based defect classification with mechanical sorting achieves validation accuracies were 94–95% in detecting defects in mango and tomato (Amna *et al*., 2023), a pure CNN based vision system for classifying mango surface - defect classification attained an accuracy of 98% (Kang and Chen, 2020). Pruning-based YOLOv4 networks in combination with NIR cameras have been exploited for real-time high accurate in-line defect detection in apple sorting while considering the tradeoff between detection performance and the high processing rate that on-line grading lines requires (Fan *et al*., 2022).

4.2 Object Detection for Fruit Counting and Robotic Harvesting

The YOLO family and Faster R-CNN are the most popular object detection architectures used for in-field fruit detection, counting and yield estimation. Previous studies have used Faster R-CNN for fruit detection and semantic segmentation for yield estimation in apple orchards (Bargoti and Underwood, 2017); recent studies have used recent versions of YOLO for the detection of apple, orange, cherry and other orchard fruits under different illumination and occlusion conditions, with mean average precision (mAP) values generally in the range of 0.85-0.98 (Tian *et al*., 2019; Sa *et al*., 2016). Deep simulated-learning methods have also been directly applied to fruit counting from imagery (Rahnemoonfar and Sheppard, 2017). The same deep-learning semantic segmentation and object detection techniques are the foundation of vision-guided robotic harvesting systems, which rely on accurate fruit recognition, localisation, and picking-pose estimation, all within a cluttered, variably lit orchard canopy, before a robotic end-effector can successfully pick a fruit.

4.3 Data Fusion Across Sensing Modalities

No single sensing technique can provide all information associated with quality, and therefore, feature-level and decision-level fusion of output from spectroscopic, imaging and other sensor technologies has been extensively employed to enhance the robustness of overall prediction. For instance, fusion of RGB and NIR image channels achieves better results for kiwifruit detection than using either channel alone, and combined tactile-sensing and Vis/NIR spectroscopy embedded in a robotic gripper was employed to evaluate mango quality non-destructively in the act of harvesting (Cortes *et al*., 2017). The general architecture towards which the field is tending for both quality or yield prediction is some version of multi-sensor fusion, which incorporates spectral, image and environmental sensor data through machine-learning or deep-learning models (Figure 2).

5. Remote Sensing, UAVs and IoT for Field-Scale Yield Prediction

In addition to sensing individual fruit, yield estimation at field and orchard scale is increasingly based on remote and proximal sensing platforms, either as a replacement or a supplement. Satellite-based vegetation indices the Normalized Difference Vegetation Index (NDVI) (Rouse *et al*., 1974; Tucker, 1979) and the Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988) are still commonly used for regional-scale crop monitoring and yield prediction.

5.1 UAV-Based Yield Estimation

UAVs provide higher spatial and temporal resolutions than satellites and have been widely applied in crop yield estimation by integrating multispectral or RGB images with machine-learning regression models (Bouguettaya *et al*., 2022). Deep-learning-based fruit counting from UAV or ground-vehicle images with networks such as Faster R-CNN (Bargoti and Underwood, 2017) and successive YOLO versions (Tian *et al*., 2019) has been empirically verified against true harvested yield in tree orchard species such as apple, orange and tart cherry. The typical range of fruit-count-to-yield correlation explained variance is 60-90%, which depends on canopy density, occlusion, and imaging geometry. The ground-based image analysis of apple fruit and tree canopy characteristics in conjunction with neural networks has also supported early, pre-harvest yield prediction (Cheng *et al*., 2017), and UAV multispectral vegetation indices combined with stacking ensemble machine learning have been used in predicting field crop yield in drought-prone, arid environment integrating spectral, meteorological and spatial variables into a single predictive model.

5.2 Machine Learning and Deep Learning for Yield Forecasting

Systematic reviews of machine-learning-based crop yield prediction literature suggests that ensemble methods (random forest, gradient boosting) and deep-learning (CNNs, LSTMs, hybrid CNN-LSTM models) perform better than single-algorithm statistical methods, especially when climatic, soil, and remote-sensing features are considered together (van Klompenburg *et al*., 2020; Oikonomidis *et al*., 2023; Chlingaryan *et al*., 2018; Cai *et al*., 2018). Integration of climate big-data and irrigation-scheduling features into deep-learning models has led to better accuracy of yield estimations under contrasting water-supply regimes, while explainable AI (XAI) methods are more and more employed to extract which environmental and management variables are the actual drivers of model prediction under unusual climate conditions a factor that is as important for grower trust and adoption as it is for model accuracy.

5.3 Wireless Sensor Networks and IoT Integration

Wireless sensor networks (WSNs) embedded in IoT structures provide continuous monitoring of soil moisture, temperature, humidity, and macronutrient levels, complementing the sporadic coverages from remote-sensing overpasses with terrestrial truth data at high temporal resolution (Ojha *et al*., 2015; Zhang *et al*., 2002). Energy-efficient designs for WSN, appropriate communication protocols (LoRa, Wi-Fi, ZigBee), cloud-based analytics platforms integration, and many more have been reviewed extensively, and soil-nutrient sensors like NPK and various others are being integrated into these networks for precision-fertilisation decisions.

Table 2. Remote- and proximal-sensing platforms used for field-scale yield prediction in fruit and vegetable production, with representative spatial and temporal characteristics.

Sensing platform	Primary use case	Typical spatial/tempora resolution	Representative reference
Satellite (Sentinel, Landsat MODIS)	Regional NDVI/vegetatior monitoring, drought/yield forecasting	10 m–1 km; days–weeks revisit	Weiss *et al.*, 2020; Tucker 1979
UAV multispectral/RGB	Field/orchard-scale yield mapping fruit counting	cm-scale; on-demand flights	Bouguettaya *et al.*, 2022 Bargoti and Underwood 2017
Ground-based machine vision	Individual fruit detection, counting defect grading	mm-cm scale continuous/real-time	Tian *et al.*, 2019; Kang and Chen, 2020
Wireless sensor networks IoT	Soil, weather and nutrien monitoring	Point-based; continuous/real-time	Ojha *et al.*, 2015; Zhang *e al.*, 2002
Robotic harvesting platforms	Fruit localisation, picking-pose estimation, integrated sensing	cm scale; real-time on-platform	Bargoti and Underwood 2017; Cortes *et al.*, 2017

6. Sensing intelligence in a changing environment and climate condition

What sets this review apart from previous ones is that it specifically addresses changes in the biological processes being sensed, along with the sensing and prediction systems, caused by changing environments. Increasing air and soil temperatures, higher atmospheric CO_2 concentration, modified water availability, and increased exposure to UV, and tropospheric ozone have been proven to alter the biochemical profile of fruits and vegetables sugar, acid, phenolic and pigment contents, to name a few as well as the canopy architecture and reflectance (Moretti *et al*., 2010; Bisbis *et al*., 2018; Booker *et al*., 2009).

6.1 Direct Effects on Fruit and Vegetable Composition

High growing-season temperatures have been associated with lower soluble solids content in certain stone fruit, and with an altered sugar/acid ratio in strawberry and tomato. Elevated CO_2 has also been related to increased sugar, and decreased protein and mineral concentration in tubers of potato, as well as to changes in the profile of flavour compounds in wine grape (Bisbis et al., 2018; Moretti *et al.*, 2010). The challenge for sensing is immediate: sugars, acids, phenolics and chlorophyll are precisely the compounds NIR, hyperspectral and fluorescence-based methods target to quantify, thus any climate-induced change in their baseline concentrations propagates directly into the reference value sets against which spectral calibration models are developed and validated.

6.2 Implications for Sensor Calibration and Model Transfer

Chemometric and machine-learning models are, by construction, tied to the range and distribution of whatever calibration dataset trained them. When produce grown under new climatic conditions falls outside that range, both spectroscopic and image-based models tend to lose accuracy an expression of the broader calibration-transfer and model-drift problem long recognised in NIR chemometrics (Alamar *et al.*, 2007; Zou *et al.*, 2010; Cortes *et al.*, 2019). Something similar happens in remote-sensing-based yield models: vegetation indices such as NDVI can respond ambiguously to combined heat and water stress, which is why composite indices a vegetation health index or crop water stress index, for example that integrate thermal and spectral information are needed to separate genuine stress signals from senescence or ordinary phenological change.

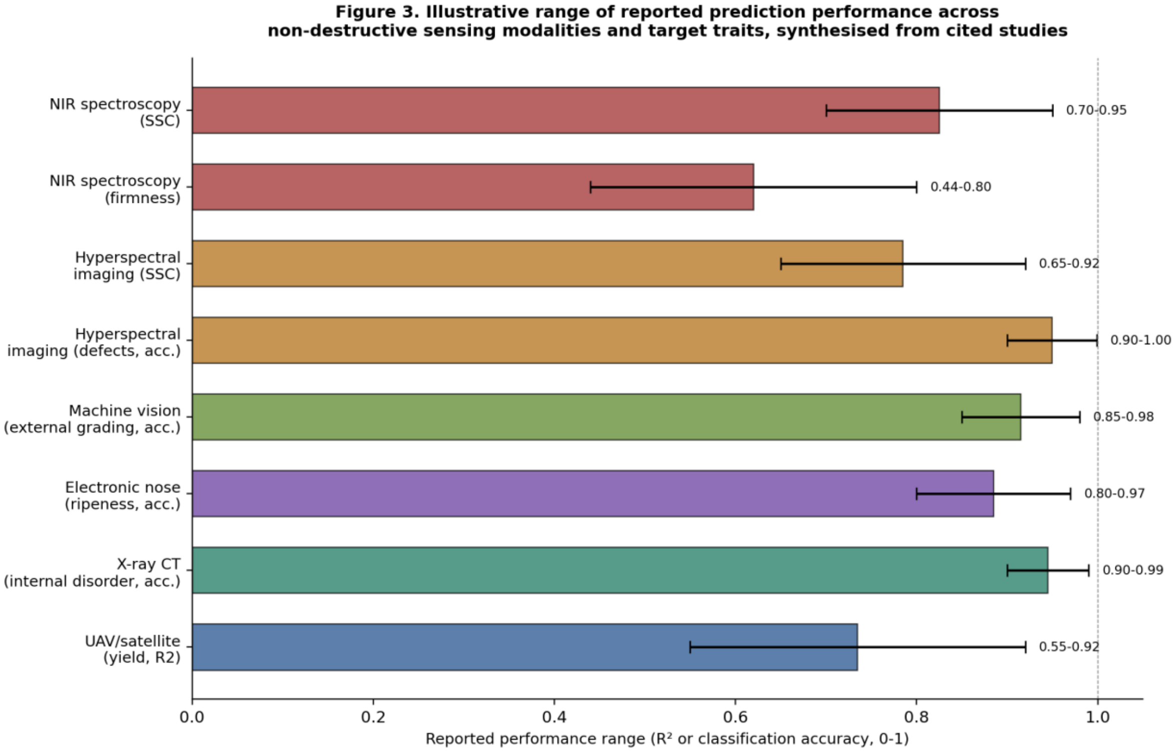

Figure 3. Reported prediction accuracies for different non-destructive sensing technologies and target traits, qualitatively summarised from the literature as cited in the review. Ranges shown vary between crops, cultivars, and environments/seasons, and are not a single meta-analytic estimate. (Original figure; refer to Table 1 for the individual studies and the R2 ranges corresponding to each modality/trait estimate.)

Reported prediction performance, as Figure 3 shows, varies considerably not only between sensing modalities but within a single modality across different target traits. Some of this variability is itself attributable to environmental and seasonal heterogeneity in the underlying calibration and validation datasets. Firmness prediction by NIR spectroscopy, for instance, has a markedly wider and lower performance range than SSC prediction does, reflecting both a less direct spectral basis and a greater sensitivity to genotype-by-environment interaction in how fruit texture develops.

6.3 Strategies for Climate-Resilient Smart Sensing

Several complementary strategies have been proposed or demonstrated for keeping sensing and prediction accuracy stable as environmental baselines shift. Calibration transfer methods – standardisation, slope/bias correction between instruments and seasons allow existing models to adapt to new data distributions without needing a full recalibration (Alamar *et al.*, 2007). Multi-sensor data fusion, combining spectral, image and environmental sensor data as summarised in Figure 2, can improve robustness by letting a model draw on complementary information sources when any one modality's baseline shifts. Explainable AI and domain-adaptation techniques, increasingly used in yield-prediction work, offer a way to detect when a model is being applied outside its valid domain and to retrain or recalibrate accordingly. Finally, treating climate and weather variables as model features rather than as noise to be filtered out has been shown to improve deep-learning yield-prediction accuracy under abnormal climate conditions, and offers a template that quality-prediction models could adopt as well.

7. Cross-Cutting Challenges

Several challenges cut across all the sensing modalities discussed here, despite how far the underlying technologies have matured. Instrument and calibration-model cost remains a real barrier to adoption, particularly for hyperspectral imaging and deep-learning pipelines that require substantial computational infrastructure; portable, LED-based Vis/NIR devices and lightweight CNN architectures are partial answers to this (Abasi *et al.*, 2018; Fan *et al.*, 2022). Calibration models also tend to be specific to a given cultivar, season and instrument, so moving a model developed on one dataset to new cultivars, growing regions or instruments usually calls for recalibration or dedicated transfer-learning methods (Cortes *et al.*, 2019). Most reported model-performance statistics, moreover, come from controlled or semi-controlled validation datasets that may not fully capture the genotype-by-environment variation seen in commercial production a gap that matters given the climate-driven compositional shifts discussed in Section 6.

Occlusion, variable illumination and canopy complexity continue to be major challenges for machine-vision based fruit counting and robotic harvesting in field conditions, even where performance (e.g., accuracy of fruit detection) is very high in controlled environments or on grading lines. Additionally, relatively few studies have systematically investigated multi-sensor fusion architectures for simultaneous quality and yield prediction; most existing literature still considers quality assessment and yield prediction as two independent problems, and formal frameworks combining both (e.g., as shown in Figure 2) are more theoretical than practically validated. The current literature also largely lacks standardised protocols for testing model robustness against deliberately varied environmental and seasonal conditions, as opposed to the standard random train/test splits within a single season a limitation that reduces the confidence for real-world deployment, especially as the climate changes.

8. Future Perspectives

Several developments seem likely to shape the next generation of smart sensing systems for fruits and vegetables. Continued miniaturisation and cost reduction of NIR and hyperspectral sensors, driven by micro-electromechanical systems (MEMS) and LED-array technology, should extend handheld and in-field deployment further, building on portable devices already validated for apple, grape and blueberry (Beghi *et al.*, 2013a; Giovenzana *et al.*, 2015). Deep-learning architectures built specifically for spectral data one-dimensional CNNs, transformer-based models are likely to increasingly supplement or replace classical PLSR pipelines, particularly once large, well-curated spectral libraries spanning multiple seasons and growing environments become available for training.

Multi-sensor and multi-modal data fusion, bringing spectroscopic, imaging, volatile-profile and environmental sensor data together within unified machine-learning frameworks, looks like a particularly promising direction for improving both accuracy and robustness to environmental variation, since complementary modalities are unlikely to fail in the same way under a given climatic perturbation. Explainable AI methods, already applied to abnormal-climate yield prediction, could be extended to quality-prediction models to work out when and why a calibration is failing under new environmental conditions, allowing more targeted recalibration. Finally, tighter integration of smart sensing outputs with genomic and phenomic breeding pipelines using fast, non-destructive phenotyping of fruit quality and yield traits to speed up selection for climate-resilient cultivars offers a way to close the loop between sensing technology and the underlying genetic improvement of climate adaptability in horticultural crops.

9. CONCLUSION

Smart sensing technologies – spanning Vis/NIR spectroscopy, hyperspectral and multispectral imaging, machine vision and deep learning, electronic nose, X-ray CT, and remote/proximal sensing for yield estimation have grown into a broad and increasingly integrated toolkit for assessing fruit and vegetable quality and yield without destroying the produce. Vis/NIR spectroscopy and hyperspectral imaging now routinely deliver strong predictive performance for soluble solids content and external defect classification, while firmness, acidity and some internal-disorder traits remain comparatively harder to predict. Machine-vision and deep-learning-based grading and object-detection systems have gone a long way toward automating both packhouse grading and orchard-scale yield estimation, and remote-sensing and IoT platforms now offer continuous, multi-scale monitoring of crop status. Even so, the accuracy and reliability of all these systems remain measurably sensitive to the environmental and climatic conditions under which their calibration and validation data were collected a challenge that will only grow as climate variability increases. Addressing it through calibration transfer, multi-sensor fusion, environmentally aware model design and standardised climate-variable validation protocols is a critical direction for making smart sensing systems reliably deployable across the increasingly variable growing conditions that fruit and vegetable production faces worldwide.

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