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Imaging solutions: Driving agri-food tech towards sustainability

Today's global food production system faces significant challenges crucial to sustaining our planet's fast-growing population. This growth requires a significant increase in the food supply, with estimates suggesting a need to boost food production by up to 70% to meet rising demand. At the same time, the need for sustainable farming practices has never been more critical. The agriculture sector contributes approximately 24% of global greenhouse gas emissions and plays a significant role in water usage and habitat loss.

These environmental impacts conflict with the European Union's sustainability goals, which aim for a climate-neutral continent by 2050. Climate change intensifies the challenges faced by the agri-food sector, heightening crops' vulnerability to pests, diseases, and extreme weather events. Additionally, roughly one-third of all food produced for human consumption is lost or wasted. To address these challenges, balancing increased food production with environmental sustainability goals is essential for the future of global food systems, highlighting the need for innovative approaches and solutions.

Photonics at the heart of the solution

Photonics and imaging technology, specifically, are crucial to addressing these challenges, offering innovative tools that transform the agri-food tech sector. Photonics-based instruments emit light toward a target, interacting with the material in ways specific to its composition and structure. The light may be absorbed, reflected, transmitted, or cause the material to fluoresce. Advanced sensors capture these interactions, providing detailed information about the target's chemical, physical, and biological makeup through sophisticated analysis.

The main benefits of photonic solutions are their non-contact, fast, and primarily non-destructive testing nature. This non-invasive approach allows for real-time monitoring and inspection of agricultural products and foodstuffs, enabling the detection of diseases, nutritional content, moisture levels, and other critical parameters without compromising sample integrity, as shown in Table 1 below.

Table 1. Overview of non-destructive methods for evaluating fruit ripeness and their correlation with internal characteristics. [1]
Abbreviations: SSC (Soluble Solids Content), DM (Dry Matter), MC (Moisture Content), TTA (Titratable Acidity), TSS (Total Soluble Solids), and WC (Water Content). Each numbers in the table are referenced in the reference section at the end of the article.

	Colorimetry	Visible imaging	Spectroscopy	Fluorescence	Hyper spectral imaging	Multispectral imaging
Apple	Color [21]	Color [22]	Chlorophyll [23], Anthocyanins [24], Carotenoids [24], Favonols [25], SSC [26], Firmness [27]	Chlorophyll [28], Anthocyanins [29], Flavonols [29], Firmness [29], SSC [29]	Firmness [30], SSC [31]	Firmness [32], SSC [33]
Pear			Firmness [34], SSC [35]		SSC [36]	
Peach	Color [37]		Firmness [38], Chlorophyll [39], Color [37]	Firmness [40]	Firmness [41]	Firmness [9], SSC
Avocado			MC [42], DM [42]		DM [43]	
Nectrarine	Color [44]		SSC [45], Firmness [45]	Firmness [40]		
Mango	Color [46]		DM [47], Starch [48], SSC [47], Color [49], Firmness [50]		Firmness [8], SSC [8], WC [8]	
Banana	Color [51]	Color [51]	TSS [52], Chlorophyll [53]		Firmness [54], TSS [54]	
Tomato	Color [55], Firmness [56], TSS [57]	Color [58], Firmness [59]	Lycopene [60], SSC [61]	Chlorophyll [62]		Phenollic [63], Lycopene [63]
Melon			SSC [64]			
Mandarin			TTA [65], SSC[66], Firmness [67], DM [68]			
Cherry	Color [69]		Firmness [70], SSC [71]			
Strawberry			Color [72], TTS [73], Firmness [72], TTA [73]		Firmness [74], TSS [75], TTA [75]	SSC [76], Firmness [77]
Apricot			SSC [78), Firmness [78], TTA [78]			
Kiwifruit			TSS [79], SSC [79], Firmness [80], DM [81], Starch content [79]			
Persimmon			SSC [82]		Firmness [83]	
Grape			SSC [84], TTA [84], Anthocyanin [85]	Chlorophyll [86], Anthocyanin [86], TSS [86], Flavonols [87]	SSC [88], TTA [88]	
Pineapple		Color [89]	DM [90], SSC [91]			
Plum			Firmness [92], SSC [93], Color [92]			

By leveraging light-matter interactions, photonics enables precise, efficient, and sustainable management practices in the agri-food sector, promoting higher yields, reduced waste, and enhanced food safety.

The following non-destructive techniques are instrumental in advancing the agri-food tech sector, providing precise and efficient tools for assessing and improving the quality, safety, and sustainability of agricultural products and food:

1. **Colorimetry & visible imaging**
2. **Visible & near-infrared (VNIR) spectroscopy**
3. **Fluorescence imaging**
4. **Hyperspectral imaging**
5. **Multispectral imaging**

1. Colorimetry & visible imaging

Colorimetry and visible imaging are essential techniques in the agricultural and food technology (agri-food tech) sector. They provide a straightforward, non-destructive means of assessing the quality and characteristics of food and farming products by measuring the intensity of light reflected from an object in the visible spectrum (approximately 400-700 nm), offering insights based on color variations and patterns.

Sensor technological advancements have enabled a shift from human evaluation to measurements in the CIELAB color space (L*, a*, b*), which offers highly accurate and consistent color measurements. The rise of RGB sensors, capable of simultaneously measuring RGB colors on a 2-D area with digital output, has further boosted colorimetry and visible imaging by offering a straightforward and cost-effective setup for many applications (see, for example, Hamamatsu S9706 [2])

Hamamatsu's S9706.

In agri-food tech, colorimetry and visible imaging are extensively used for quality control and sorting processes. For example, in the fruit and vegetable industry, these technologies enable the automated sorting of products based on ripeness, color uniformity, and surface defects. In apple orchards, colorimetry determines the optimal harvest time by assessing the apple color development, ensuring that only fruits meeting specific maturity criteria are picked. This maximizes the quality and taste of the harvested fruits and reduces waste by minimizing the picking of underripe or overripe produce. Similarly, in grain quality assessment, visible imaging helps to identify and segregate grains infected by fungi or showing signs of sprouting, thereby improving the safety and quality of the grain supply.

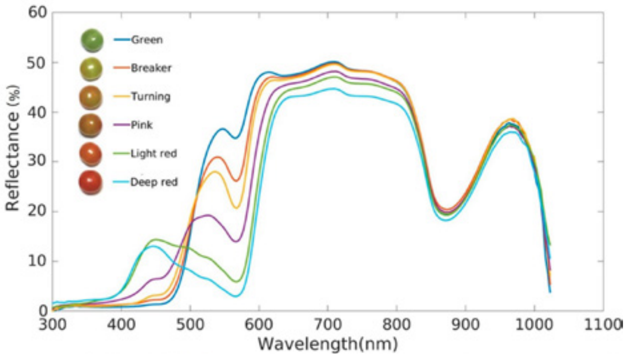
2. Visible & near-infrared spectroscopy

Compared to the previous technique, visible and near-infrared (VNIR) spectroscopy offers a more nuanced and in-depth analysis tool in the agri-food tech sector. VNIR spectroscopy extends analysis into the near-infrared range (approximately 400-2500 nm), tapping into the unique ways materials interact with light across both visible and NIR wavelengths. This spectral range is particularly insightful because molecular vibrations and overtones, indicative of chemical bonds in organic compounds, strongly absorb NIR light, allowing precise identification of chemical compositions and concentrations within agricultural products and foods.

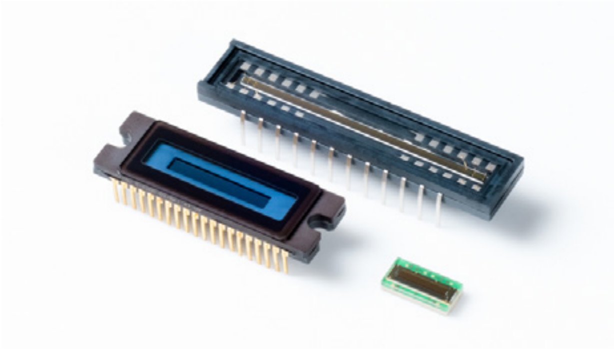
VNIR spectroscopy enables the detection and quantification of organic compounds and moisture content with high sensitivity and specificity. For example, in precision agriculture, VNIR spectroscopy can analyze crop foliage to determine nitrogen levels, directly impacting fertilization decisions crucial for crop yield optimization.

As seen in Graph 1 below, in food quality assessment, VNIR spectroscopy is used to quantify the sweetness of fruits such as apples and berries by measuring sugar content directly through their skin. This allows for sorting into different quality grades without damaging the produce.

Graph 1: Typical progressive change of reflectance spectra at different ripening stages of tomato [3]



The same physical principle can be used to study the in-line defectivity of food products, combining both sensors working in the visible spectrum (Hamamatsu CCD Sensors[4]) and sensors working in the infrared spectrum (Hamamatsu InGaAs Sensors[5]).

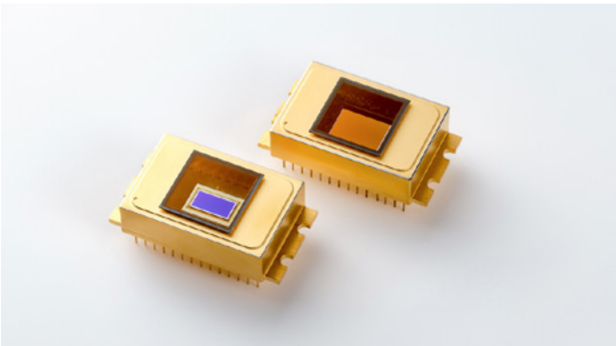


Hamamatsu's CCD sensors

Thus, VNIR spectroscopy's ability to provide rapid, non-destructive analysis across various samples makes it an invaluable tool for real-time monitoring and quality control in food production.

3. Fluorescence imaging

Building on the depth of analysis provided by VNIR spectroscopy, fluorescence imaging introduces a dynamic dimension to the agri-food tech sector's toolkit. Fluorescence imaging relies on the ability of certain substances to absorb light at one wavelength and emit it at another, longer wavelength. To detect even small amounts of markers, accurate and highly sensitive sensors at different wavelengths are mandatory, like Hamamatsu InGaAs area sensors [6].

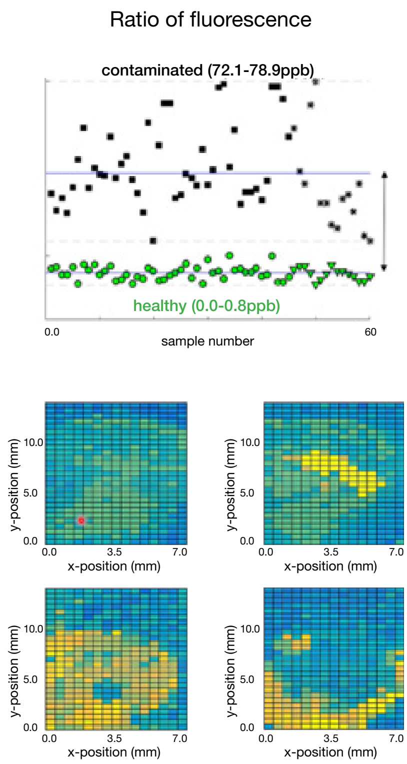


Hamamatsu's InGaAs area sensors

Fluorescence imaging applications in agri-food tech range from detecting microbial contamination in food products to assessing plant health. For instance, specific pathogens on fruit skins can be identified through their distinct fluorescence signatures, enabling early detection of spoilage and contamination without physical contact. Similarly, fluorescence imaging can identify areas of stress in crops caused by drought or disease by observing changes in chlorophyll fluorescence, which correlates with the plant's photosynthetic activity and overall health.

A particularly impactful application has been the rapid screening of mycotoxins in grains and nuts, posing significant health risks. Fluorescence imaging can detect these toxins with high sensitivity, often enabling detection levels down to parts per billion. This capability significantly enhances food safety protocols, allowing for the precise identification and removal of contaminated products from the supply chain.

Graph 2: Fluorescence spectroscopy enabling toxin detection[7]



4. Hyperspectral imaging

With modern sensors, it is now possible to combine the aforementioned techniques and collect a complete continuous spectrum for each pixel, using it for hyperspectral imaging. This comprehensive spectral data enables the detailed characterization of agricultural products and foods' chemical and physical makeup by detecting subtle differences in light absorption and reflection patterns. It can identify and quantify various substances and conditions, from crops' moisture content and protein levels to subtle signs of diseases and nutrient deficiencies not visible to the naked eye.

In precision agriculture, hyperspectral imaging mounted on unmanned aerial vehicles (UAVs) can map variability in soil properties across a field, enabling targeted fertilization and irrigation that enhance crop yield and reduce resource use. In food quality assessment, this technology can detect foreign bodies or contamination, such as bits of plastic or metal, and monitor the freshness and ripeness of produce without damaging it.

Graph 3: Hyperspectral imaging assessment of different coffee bean types.

Hamamatsu's Energetiq tuneable light sources (LDTLS®) and InGaAs cameras were utilized to demonstrate the imaging.

Due to the level of detail provided by hyperspectral imaging and the availability of integrated hyperspectral cameras, such as the SXGA InGaAs Camera [8], its application is continually expanding. It offers a potent tool for advancing the efficiency, sustainability, and safety of food production.

Multispectral imaging's balance between spectral detail and operational simplicity makes it an invaluable tool in agri-food technology. Its focused, rapid analysis capabilities facilitate sustainable farming practices and enhance food quality.

Hamamatsu's SXGA InGaAs Camera

Imaging tools are critical to a more sustainable agri-food tech sector

As global food demands rise and the need for sustainable agriculture intensifies, imaging technologies emerge as essential allies in the agri-food tech sector. These technologies serve a dual purpose: enhancing productivity and sustainability in food production and processing. They enable non-destructive, precise analysis of crops and food products, offering valuable insights into quality, safety, and environmental impact. They facilitate crop health monitoring, resource optimization, and waste reduction and address critical challenges in the agri-food sector. Integrating imaging technologies is key to achieving higher yields, reducing environmental footprint, and ensuring food safety and quality.

As these technologies evolve and become more accessible, they will play an increasingly significant role in sustainably meeting the world's food production needs, addressing immediate agricultural challenges, and paving the way for future advancements in global food supply and environmental care.

Please contact Hamamatsu Photonics Europe for advice on your agri-food needs: info@hamamatsu.eu

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