Agri-food: which technologies to guarantee our health?

A. Sortino¹, G. De Leo², T. Caruso³, A. Zinnai⁴ and F. Beltrame^{1,5,a}

¹ENR - The National Institution of Italy for Standardization Research and Promotion, Palermo, Italy; ²College of Allied Health Sciences, Augusta University, Augusta, Georgia, USA; ³Università degli Studi di Palermo, Palermo, Italy; ⁴Univesità di Pisa, Pisa, Italy; ⁵Università degli Studi di Genova, Genova, Italy.

Abstract

In an international and constantly evolving market, the agri-food is an important economic sector for countries, like Italy, that are in the Mediterranean region. In recent years, smart digital technologies, machine learning, and big data have been playing an important role in improving the physical production of goods and the quality of operations of the agriculture sector. For example, sensors that a few decades ago were available only in small research greenhouses, now can be deployed in agricultural fields. The information they can transmit over the internet can be used to make real time adjustments to the various steps needed to harvest an agriculture product. Ultimately, the digital solutions applied to agriculture aim to limit waste while minimizing human labour. The "From farm to fork" strategy of the European Green Deal identifies digital technologies as the tools to achieve greater agricultural sustainability. In order to guarantee greater profitability, once a quality agriculture product has been harvested, it is necessary to enhance it by certifying its origin and by disclosing the methods used to produce it and by reporting on the safeguard systems adopted. For these reasons, it is vital to follow agricultural standards that can give the product a certification of quality. For example, data analysis, smart labels, blockchain and smart contracts, that follow standardized protocols, are tools that, in addition to certifying the origin of a product, can reduce brokerage costs, improve deliver time, maintain persistent quality while minimizing human errors. In this study we conducted a literature review on the articles published in last two International Symposia on Mechanization, Precision Horticulture, and Robotics with a focus on innovative technologies and their fields of application developed for the agri-food sector. An overview of the impact of implementing and following standardization practices is presented as well.

Keywords: agri-food, sustainability, sensors, standardization

INTRODUCTION

The new common agricultural policy and the "From farm to fork" strategy of the European Green Deal identify digital as the tool to achieve greater agricultural sustainability. The growing world population is generating more and more demands for food production. The technology applied to agriculture aims to limit waste and lighten man's work. Farmers have understood how technological innovations such as sensors, apps and information transmitted over the internet can help them (Hung et al., 2016). Advances in electronic and computer science research are impacting the quantity and quality of horticultural production by improving economic, environmental and social sustainability. Major areas of recent research include hyperspectral sensing, computer vision, artificial and convolutional neural networks, and unmanned aerial vehicle (UAV). These components and systems are developed for a wide variety of horticultural products including citrus fruits, apples, potatoes, tomatoes and ornamental plants (Schueller, 2020).

Drones have replaced the human eyes and sensors make decisions that result in saving water, energy and labour. Technological innovations are creating a different way to farm that attracts a new generation of agronomists and engineers who work together (Cerbini, 2022).

^aE-mail: francesco.beltrame@unige.it



Acta Hortic. 1360. ISHS 2023. DOI 10.17660/ActaHortic.2023.1360.15 XXXI IHC – Proc. III International Symposium on Mechanization, Precision Horticulture, and Robotics: Precision and Digital Horticulture in Field Environments Eds.: S. Sankaran and D. Rousseau

Agriculture 4.0 is the evolution of precision agriculture. Agriculture 4.0 uses Internet of Things (IoT), big data, artificial intelligence and robotics to extend, speed up, and increase the efficiency of activities that impact the entire production chain. In 2020 agriculture 4.0 in Italy generated around 540 million euros, with a growth of 20% compared to 2019. (Aquaro, 2022). The goals of this paper were: 1) to summarize the technological innovations and their fields of application that have been presented at the last two International Symposia on Mechanization, Precision Horticulture, and Robotics; 2) to highlight how standardization efforts can contribute to the grow of the agri-food sector by reducing brokerage costs, improving deliver time, maintaining persistent quality while minimizing human errors.

MATERIALS AND METHODS

This literature review is based on articles published during the first and second International Symposium on Mechanization, Precision Horticulture, and Robotics: Precision and Digital Horticulture in Field Environments, held respectively in Brisbane (Australia) in 2014 and in Istanbul (Turkey) in 2018. The articles that presented a simple overview of innovative technologies in horticulture and the articles that offered ideas on possible innovations were excluded. Only articles that presented practical innovations were taken into consideration. Subsequently, the articles were grouped according to the field of application and the technological innovation presented. All the articles presented at the conferences were collected and published after two years in the journal *Acta Horticulturae*, respectively in volumes 1130 and 1279.

RESULTS AND DISCUSSION

Twenty-five articles were identified. Table 1 summaries the results by identifying the first author of the study and the year of publication in the first column. The second column of Table 1 shows the field of application, the third columns the agri-food focus and the last column the technology presented.

Seven articles focused on fruit quality monitoring (Onwude et al., 2020; Percival et al., 2016; Xu et al., 2016; Bargoti et al., 2016; Underwood et al., 2016; Layden and O'Halloran, 2016; Robson et al., 2016), four articles presented the estimation of the yield of fruit trees (Sarron et al., 2020; Bresilla et al., 2020; Payne et al., 2016; Hung et al., 2016), four articles were centred on the water status of crops (Delalande et al., 2020; Coulombe et al., 2020; Montoya et al., 2020; Camps et al., 2020), two articles on crop disease detection (Ampatzidis et al., 2020; Atshan et al., 2020), three articles on precision viticulture (Poblete-Echeverría et al., 2020; Gatti et al., 2020a, b), one article focused on tree thinning (Pflanz et al., 2016), two articles focused on the amount of nitrogen in trees (Perry et al., 2016; O'Connell et al., 2016), and two articles presented mechanization in horticultural applications (Patten et al., 2016; Hemming et al., 2016).

Robot

Automation is one of the new frontiers of agricultural mechanization and it has the potential to revolutionize the work in the fields and to provide some of the answers to the needs for greater competitiveness, productivity and sustainability of modern companies. Having agricultural machines and robots that autonomously carry out agronomic operations allows to reduce the use of fertilizers and pesticides and to improve the safety of farmers who do not have to be exposed to risky situations or chemicals that are potentially harmful for their health. Robotics and automation are helping to make high-resolution, timely, farm-level measurements for tasks such as yield estimation, crop health and soil analysis. Robotics and intelligent sensing systems can provide useful information to improve yield and quality in the production of specialty crops. A mobile land robot with a scanning lidar (laser range sensor) can build a three-dimensional (3D) model of an orchard by associating data from individual trees and deriving algorithms to automatically detect and segment each tree (Underwood et al., 2016). Mechanization in horticulture tends more and more to automation. It is an unstoppable evolution, useful to simplify man's work and/or necessary to make it possible, fast and accurate. Vegetable production is characterized by intense traffic, especially during

harvesting. A group of researchers studied a multi-robot system for horticulture applications (Patten et al., 2016). Another study ran experiments for robotic harvesting of sweet pepper fruits, solving the problem of reaching, grabbing and detaching the fruit efficiently, without damaging it (Hemming et al., 2016). Wine industries are susceptible to the impacts of climate change and associated stresses, including water scarcity. One approach to provide alternative solutions to the sector is to invest in technological solutions for better vineyard management. The use of technologies, such as robots and sensors, to monitor vineyards offers solutions to support vineyard management decisions. A group of researchers developed a remote-controlled robot prototype that was tested in the vineyards in combination with a series of sensors (laser LiDAR scanner, non-contact electromagnetic induction device, thermal cameras and high-definition cameras) with the goal of collecting information through the seasonal trend (Poblete-Echeverría et al., 2020).

Study	Field of application	Agri-food focus	Technological innovation
Sarron et al., 2020	Estimation of the yield of fruit trees	Mango fruits	Algorithm, digital imaging
Bresilla et al., 2020	Estimation of the yield of fruit trees	Apple trees	Algorithm
Onwude et al., 2020	Fruit quality monitoring	Sweet potatoes	Digital imaging
Ampatzidis et al., 2020	Crop disease detection	Grapevine	Artificial intelligence, machine learning
Poblete-Echeverría et al., 2020	Precision viticulture	Grapevine	Robot, sensors
Delalande et al., 2020	Water status of crops	Apple trees	Sensors
Gatti et al., 2020a	Precision viticulture	Grapevine	Sensors
Gatti et al., 2020b	Precision viticulture	Grapevine	Sensors
Atshan et al., 2020	Crop disease detection	Pepper crops	Sensors
Coulombe et al., 2020	Water status of crops	Chili pepper	Sensors, digital imaging
Montoya et al., 2020	Water status of crops	Indoor plants	Sensors
Camps et al., 2020	Water status of crops	Tomatoes and aubergines	Algorithm
Percival et al., 2016	Fruit quality monitoring	Wild blueberry	Sensors
Patten et al., 2016	Mechanization in horticultural applications	Crop fields	Algorithm, robot
Xu et al., 2016	Fruit quality monitoring	Blueberries	Sensors
Bargoti et al., 2016	Fruit quality monitoring	Apple trees	Unmanned vehicle
Underwood et al., 2016	Fruit quality monitoring	Almond trees	Robot, sensors
Layden and O'Halloran, 2016	Fruit quality monitoring	Plants of carrots, sweet corn	Sensors
		and green beans and strawberries	
Pflanz et al., 2016	Thinning of trees	Apple trees	Sensor, geographic information system
Robson et al., 2016	Fruit quality monitoring	Avocado fruits	Sensor, geographic information system
Payne et al., 2016	Estimation of the yield of fruit trees	Mango fruits	Digital imaging
Perry et al., 2016	Control of the amount of nitrogen in trees	Apple and pear trees	Sensors, unmanned vehicle
Hemming et al., 2016	Mechanization in horticultural applications	Pepper harvest	Robot
O'Connell et al., 2016	Control of the amount of nitrogen in trees	Almond tree	Sensors
Hung et al., 2016	Estimation of the yield of fruit trees	Apple, mango, lychee and almond orchards	Algorithm, robot

Table 1. Literature review summary.

The 25 identified articles can also be classified according to the type of technological innovation presented.

Sensors

Sensors help to assess the health of crops, which will allow farmers to program targeted



treatments. Sensors are critical to detect the state of the soil, and they can plan adequate water irrigations. A group of researchers in collaboration with vegetable (carrot, sweet corn and green bean) and strawberry producers, validated Greenseeker[®] biomass sensors together with remote sensing and variable speed or prescription mapping. The goal was to try to improve market yield through early detection of crop stress or poor performance due to biotic and abiotic factors. (Layden and O'Halloran, 2016). Sensor technologies can be used in wild blueberry production that apply pest control products precisely to targeted areas of interest only (Percival et al., 2016). An article investigated the impacts in commercial blueberry packaging lines that could cause impact damage to blueberries that will result in fruit bruising. The impacts were quantitatively measured using a miniature instrumented sphere (Xu et al., 2016). Irrigation is one of the most important inputs into horticultural production systems, but current management practices generally do not allow for the precise delivery of irrigation inputs where and when they are required within a crop. High resolution sensors for the accurate calculation of vegetation and/or stress indices (e.g., NDVI, GNDVI, MCARI2, PRI) that reveal phenotypic changes in the structure of individual vegetation cover and/or leaf functions were investigated (Delalande et al., 2020). Two articles studied remote sensing platforms for the description and management of precision viticulture, in a 'Barbera' vineyard located in the Colli Piacentini wine district (Gatti et al., 2020a, b). A low-cost open-source microcontroller platform, Arduino, was used to monitor and to control several variables in food production systems (Montoya et al., 2020). Disease control is a key aspect for crop production and early detection of disease incidence is therefore an important aspect of crop management. Visual assessment of cultures is the most used approach, but it is costly especially at low levels of infection. Another study investigated the potential of sensor technologies to detect diseases in a pepper crop earlier than is currently possible with visual assessment (Atshan et al., 2020). The amount of nitrogen in crops affects the growth and yield of trees, so knowing the state of nitrogen is important to optimize nutrient management, minimize input costs and avoid environmental pollution. A study evaluated the use of remote sensing to assess the amount of nitrogen in the canopy through the canopy chlorophyll concentration index of apple and pear trees (CCCI) (Perry et al., 2016). Another study made satellite estimates of nitrogen status for potential application to orchard fertilization programs to overcome existing cost and sample size limits and to account for the effects of vegetation cover (O'Connell et al., 2016).

Geographic information system (GIS)

Over the last few years, GIS software application have been used in the applications of geomatics, that is the discipline that integrates the study of the territory and the environment with information technology, and which also includes territorial information systems. GISs are attracting the interest of an ever-growing audience, especially as a decision support tool. A study used satellite imagery, Geographic Information Systems and Google Earth to audit trees and to define the spatial variability of 'Hass' avocado tree conditions in Childers, Australia (Robson et al., 2016). Producing fruit that provides high quality, good shelf life and consistent long-term yields requires adjusting the crop load on fruit trees by reducing the number of flowers. Thinning is important to produce high quality fruit with adequate size. Hand thinning contributes a large part to the total cost of production, as hand thinning is labour-intensive and labour costs are rising. A group of researchers studied a new mechanical system for flower thinning that combines a camera-based sensor to identify the density of flowers in situ and a mobile geographic information system (Pflanz et al., 2016).

Artificial intelligence

Artificial intelligence is the ability of a computer system to mimic human cognitive functions such as learning and problem solving. Artificial intelligence methods can be used by agricultural robots to locate and scan territories and crops, to recognize the type of plant and to monitor its status in real time by acquiring images and collecting sensory data such as temperature, humidity, or pH level of the soil. Machine learning is considered a subset of artificial intelligence. Therefore, cost-effective alternative approaches for the early detection of diseases and parasites are desirable. A study presented a vision-based support tool for yellow grapevine (GY) disease detection using artificial intelligence (AI) and machine learning (ML) (Ampatzidis, et al., 2020).

Digital imaging

Aerial photography and satellite imagery are used to monitor areas. Since the images are acquired frequently, it is possible to identify, without human intervention, the cultivated crops and monitor certain agricultural practices. Red Green Blue (RGB) imaging can be used to monitor sweet potato quality during drying and demonstrated that RGB imaging can serve as a non-destructive tool to detect changes in agricultural product quality during drying (Onwude et al., 2020). In recent years, with the increase in agricultural production, the need for more precise tools and practices has increased. One of these practices is the estimation of the number of fruits in the tree. Numerous studies have provided fruit tree yield estimates based on machine learning with high levels of efficiency. An efficient machine learning method for detecting ripe mango fruit from RGB images and tested under heterogeneous field conditions for estimating tree yield was developed in Senegal (Sarron et al., 2020). Multispectral and thermal imagery was assessed to directly assess crop water status on a spatial scale not possible with current soil sensor probe systems, and thus helped improve irrigation decision making (Coulombe et al., 2020). Several image processing algorithms were evaluated for mango crop load determination, including hyperspectral and thermal imaging, but with preference for RGB imaging (Payne et al., 2016).

Algorithm

Over the past decade, machine learning algorithms have demonstrated its potential for detecting and counting plant organs, for improving crop quality and increase sustainability. These algorithms favour the creation of an optimal environment for agriculture, without chemicals and pesticides, in order to eliminate waste and sources of pollution. Computer vision techniques such as oriented gradient histogram and edge detection were used to extract features and recognize fruit based on shape and colour (Bresilla et al., 2020). A system consisting of ground-based robots and processing software was used to estimate fruit yield. The robots collected image data, which was automatically processed using algorithms in a software pipeline (Hung et al., 2016). A group of researchers recorded and analysed the non-invasive "Electroplantogram" EPGs of tomatoes and aubergines to detect the water deficit of plants in real time, in order to improve the efficiency of crop management (Camps et al., 2020).

Unmanned vehicle

Remote control systems, or more common drones, represent a particularly useful and very popular technology, as it allows farmers to fly over a field and collect detailed images from analysis for the most diverse purposes such as the level of ripeness of fruits or the onset of a disease on a plant. Close-up images obtained from multiple perspectives can be used to generate three-dimensional representations of the plant. A group of researchers investigated an efficient means of storing and processing information resulting from the discretization of individual trees using an unmanned land vehicle that captured three-dimensional laser beam data and image data on rows of orchards (Bargoti et al., 2016).

CONCLUSIONS

Appropriately integrated digitalization and sustainability can offer a safe path from field to fork. It is known that the quality of the final product strongly depends on compliance with certain standards, often disregarded because the individual steps are affected by factual transparency. Standards are a common language that allows researchers, people, public institutions and industry to communicate, produce and market products and services. Once a quality product has been obtained, in order to obtain greater revenues, it is necessary to enhance it, certifying the origin of the product, the methods used, and the safeguard systems adopted. Hence the importance of standardization throughout the agri-food sector, an essential requirement for the achievement of the corresponding quality certifications



downstream. Data analysis, blockchain and smart labels are tools that, in addition to certifying the origin, make procedures faster, standardized and therefore less subject to human error. Standards will be key to achieving the green and digital transitions of our economy.

The European Green Deal and the Industrial Strategy for Europe make it clear that developing new standards will be essential to strengthen the competitiveness of industry, build a sustainable future and shape a Europe fit for the digital age. Standards also allow for the interoperability of technologies and materials: as a standard provides details on the use and content of a technology or material, it is much easier to know when and how it can be used in conjunction with other technologies (EC, 2022).

Literature cited

Ampatzidis, Y., Cruz, A., Pierro, R., Materazzi, A., Panattoni, A., De Bellis, L., and Luvisi, A. (2020). Vision-based system for detecting grapevine yellow diseases using artificial intelligence. Acta Hortic. *1279*, 225–230 https://doi.org/10.17660/ActaHortic.2020.1279.33.

Aquaro, P. (2022). L'agricoltura 4.0 Vale il 4% del Giro Mondiale (Italia: Corriere della Sera).

Atshan, L., Brown, P., Xu, C., and White, S. (2020). Early detection of disease infection in chilli crops using sensors. Acta Hortic. *1279*, 263–270 https://doi.org/10.17660/ActaHortic.2020.1279.38.

Bargoti, S.U., Nieto, J., and Sukkarieh, S. (2016). Trunk localisation in trellis structured orchards. Acta Hortic. *1130*, 625–630 https://doi.org/10.17660/ActaHortic.2016.1130.93.

Bresilla, K., Perulli, G., Boini, A., Morandi, B., Grappadelli, L., and Manfrini, L. (2020). Comparing deep-learning networks for apple fruit detection to classical hard-coded algorithms. Acta Hortic. *1279*, 209–216 https://doi.org/10.17660/ActaHortic.2020.1279.31.

Camps, C., Plummer, C., and Wallbridge, N. (2020). Non-invasive "Electroplantogram" (EPG) of greenhouse crops for real-time detection of water deficit. Acta Hortic. *1279*, 303–310 https://doi.org/10.17660/ActaHortic.2020. 1279.43.

Cerbini, L. (2022). Droni a Guardia dei Campi e Irrigazioni Anti-Spreco, ecco il Contadino Digitale (Italia: Corriere della Sera).

Coulombe, J., Brown, P., White, S., Xu, C., and Koech, R. (2020). Detection of crop water status using UAV mounted sensor. Acta Hortic. *1279*, 271–278 https://doi.org/10.17660/ActaHortic.2020.1279.39.

Delalande, M., Gómez-Candón, D., Coupel-Ledru, A., Labbé, S., Costes, E., and Regnard, J. (2020). Do multispectral and thermal IR high-resolution UAS-borne imagery help in phenotyping the tree response to water stress at field? Case studies in apple diversity population and varietal assays. Acta Hortic. *1279*, 239–246 https://doi.org/10. 17660/ActaHortic.2020.1279.35.

EC. (2022, February 2). Communication from the Commission to the European Parliament, The Council, the European Economic and Social Committee and the Committee of the Regions. *Com(2022) 31 Final*. Brussels.

Gatti, M., Garavani, A., Squeri, C., Frioni, T., Dosso, P., and Poni, S. (2020a). Long-term assessment of variable rate N-fertilization in a *Vitis vinifera* L. 'Barbera' vineyard. Acta Hortic. *1279*, 255–262 https://doi.org/10.17660/ActaHortic.2020.1279.37.

Gatti, M., Squeri, C., Kleshcheva, E., Garavani, A., Vincini, M., and Poni, S. (2020b). Studying spatial and temporal variability of a 'Barbera' vineyard with traditional and precision approaches. Acta Hortic. *1279*, 247–254 https://doi.org/10.17660/ActaHortic.2020.1279.36.

Hemming, J., Van Tuijl, B., Gauchel, W., and Wais, E. (2016). Field test of different end-effectors for robotic harvesting of sweet-pepper. Acta Hortic. *1130*, 567–574 https://doi.org/10.17660/ActaHortic.2016.1130.85.

Hung, J.P., Underwood, J.P., Nieto, J., and Sukkarieh, S. (2016). Autonomous intelligent system for fruit yield estimation. Acta Hortic. *1130*, 545–550 https://doi.org/10.17660/ActaHortic.2016.1130.82.

Layden, I., and O'Halloran, J. (2016). Validating the potential of precision technology in Queensland vegetable and strawberry production. Acta Hortic. *1130*, 613–618 https://doi.org/10.17660/ActaHortic.2016.1130.91.

Montoya, A., Kacira, M., and Obando, F. (2020). Design and implementation of a low cost microcontroller in controlled environment agriculture. Acta Hortic. *1279*, 287–294 https://doi.org/10.17660/ActaHortic.2020.1279. 41.

O'Connell, M., Whitfield, D., and Abuzar, M. (2016). Satellite remote sensing of vegetation cover and nitrogen status in almond. Acta Hortic. *1130*, 559–566 https://doi.org/10.17660/ActaHortic.2016.1130.84.

Onwude, N., Hashim, N., Abdan, K., Janius, R., Che Adan, S.N., and Jalaluddin, A. (2020). RGB imaging for monitoring

quality parameters of sweet potato during drying. Acta Hortic. 1279, 217–224 https://doi.org/10.17660/ ActaHortic.2020.1279.32.

Patten, T., Fitch, R., and Sukkarieh, S. (2016). Multi-robot coverage planning with resource constraints for horticulture applications. Acta Hortic. *1130*, 655–662 https://doi.org/10.17660/ActaHortic.2016.1130.97.

Payne, A., Walsh, K., and Subedi, P. (2016). Automating mango crop yield estimation. Acta Hortic. *1130*, 581–588 https://doi.org/10.17660/ActaHortic.2016.1130.87.

Percival, G.L., Brown, G.L., and Harrington, T. (2016). Vegetation management in wild blueberry production using spectral and guidance system technologies. Acta Hortic. *1130*, 663–668 https://doi.org/10.17660/ActaHortic. 2016.1130.98.

Perry, E., Bluml, M., Goodwin, I.C., Cornwall, D., and Swarts, N.D. (2016). Remote sensing of N deficiencies in apple and pear orchards. Acta Hortic. *1130*, 575–580 https://doi.org/10.17660/ActaHortic.2016.1130.86.

Pflanz, M., Gebbers, R., and Zude, M. (2016). Influence of tree-adapted flower thinning on apple yield and fruit quality considering cultivars with different predisposition in fructification. Acta Hortic. *1130*, 605–612 https://doi.org/10.17660/ActaHortic.2016.1130.90.

Poblete-Echeverría, C., Strever, A., Barnard, Y., and Vivier, M. (2020). Proximal detection using robotics for vineyard monitoring: a concept. Acta Hortic. *1279*, 231–238 https://doi.org/10.17660/ActaHortic.2020.1279.34.

Robson, A., Petty, J., Joyce, D., Marques, J., and Hofman, P. (2016). High resolution remote sensing, GIS and Google Earth for avocado fruit quality mapping and tree number auditing. Acta Hortic. *1130*, 589–596 https://doi.org/10. 17660/ActaHortic.2016.1130.88.

Sarron, J., Sané, C., Borianne, P., Malézieux, E., Nordey, T., Normand, F., Diatta, P., Niang, Y., and Faye, E. (2020). Is machine learning efficient for mango yield estimation when used under heterogeneous field conditions? Acta Hortic. *1279*, 201–208 https://doi.org/10.17660/ActaHortic.2020.1279.30.

Schueller, J.K. (2020). Computer and electronic research trends for horticulture. Acta Hortic. *1279*, 191–194 https://doi.org/10.17660/ActaHortic.2020.1279.28.

Underwood, J., Jagbrant, G., Nieto, J., and Sukkarieh, S. (2016). Tree centric localisation in almond orchards. Acta Hortic. *1130*, 619–624 https://doi.org/10.17660/ActaHortic.2016.1130.92.

Xu, R., Li, C., Takeda, F., and Krewer, G. (2016). Blueberry packing line impact evaluation using a miniature instrumented sphere. Acta Hortic. *1130*, 639–646 https://doi.org/10.17660/ActaHortic.2016.1130.95.

