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Viticulture and wine production: challenges, opportunities and possible implications

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Abstract. Many agricultural sectors evaluate what advancements can be incorporated into their businesses to offer management support as technology keeps developing and advancing. This is especially essential to the wine business, as climate change and fluctuating atmospheric conditions, compacted seasons, drought, heat, labour shortages, and increasing production costs are all posing challenges to farmers in various parts of the world. This article aims to highlight different applications of viticulture based on digital techniques. The research will evaluate how these techniques offer opportunities for winemakers in response to increased environmental problems. The application of various proximal and remote sensing technologies has enhanced the knowledge of vineyard variation regarding geographical disparities and sequential dynamics and the underlying reasons for such variation. The study shows how knowing this information allows winemakers to use ideas more effectively through specific applications and harvest fruit packages strategically based on yield and/or fruit quality requirements and product requirements. Reduced input costs, higher efficiencies, and a better end product are all economic benefits of each of these outcomes. Since smart sensing techniques have an immense opportunity for producers at all stages, their implementation and regular use will be centered on accessible operating system and devices and the cost of integrating decision-support systems on a field scale. Data rights and security, especially when data is obtained through third parties, is a problem that must be addressed in the coming years to enable the widespread adoption of such technology.

1 Introduction

Many agricultural sectors evaluate what advancements can be incorporated into their businesses to offer management support as technology keeps developing and advancing (Fountas, Espejo-García, Kasimati, Mylonas, & Darra, 2020). This is especially essential to the wine business, as climate change and fluctuating atmospheric conditions, compacted seasons, drought, heat, labour shortages, and increasing production costs are all posing challenges to farmers in various parts of the world (Koufos, Mavromatis, Koundouras, & Jones, 2020; Soar, Sadras, & Petrie, 2008). As a result, there is a growing need to analyze

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vineyard management approaches by regularly monitoring biophysical factors and grapevine performance. A set of technology is now accessible that allows winemakers to access and use precise data and information about their vineyards as a basis for making the best decisions possible in terms of keeping productive while also remaining environmentally and financially viable. This toolkit includes remote and proximal sensing technologies, GPS, GIS, geostatistics, AI, and DSS. Precision or digital viticulture are often used in the viticulture industry to denote the wise development and deployment of such techniques (Ammoniaci, Kartsiotis, Perria, & Storchi, 2021).

In wine grape production systems, non-invasive sensing techniques like as spectroscopy, MSI, HSI, Chl fluorescence, thermography, ER, LiDAR, and CV can be used to collect essential data about the vineyard and the plants growing within it (Fountas, Mylonas, et al., 2020). They can be utilized as transportable sensors or installed on or integrated into ground-based platforms including piloted vehicles, automated robotic systems, and machinery, as well as aerial platforms like satellites, light aircraft, and UAVs or drones (Matese & Di Gennaro, 2018; Matese et al., 2015). Moreover, the broad availability of cellphones and "apps" has revolutionized the way producers can access and measure vine performance and fruit qualities in the vineyard. Many vineyard operations will likely be mechanized in the future thanks to the employment of specially built robotic devices with non-invasive sensing technology (Matese et al., 2015; Suarez et al., 2021).

Grape producers can track change in vine parameters such as canopy size (Sanz et al., 2018), as well as water (Gutiérrez, Diago, Fernández-Novales, & Tardaguila, 2018) and nutritional status (Diago et al., 2016), yield (Aquino, Millan, Diago, & Tardaguila, 2018), grape composition (Gutiérrez, Tardáguila, Fernández-Novales, & Diago, 2019), and disease infection (Mahlein et al., 2019) using these spatially enabled digital technologies. The potential to trace the geographical distribution in the vine, soil and geographical aspects across vineyards also allows wine makers to more efficiently apply inputs like fertilizers, sprays, and irrigation water through targeted applications, as well as harvest fruit parcels selectively according to different yield and/or fruit quality standards and product specifications (Bramley, Ouzman, & Trought, 2020).

The purpose of this article is to highlight different applications of viticulture based on digital techniques, either locally available or under process. The research will evaluate how these techniques offer opportunities for grape production and winemakers in response to increased environmental problems, including alterations in climatic and soil conditions. The goal is to enhance the working capacity of the procedures involved in winemaking and reduce production costs. The research will also highlight the operation of different sensing techniques and the possible implication of artificial intelligence in viticulture.

2 Methods

The present and future implementation of sensing techniques in viticulture are deliberated in terms of soil characteristics and quality, biomass yield, canopy architecture, nutrient and water status, pests and diseases, agricultural prediction, yield and fruit composition, vineyard sampling, targeted management, and selective harvesting. Table 1 summarizes the main opportunities and challenges of these technologies in viticulture.

Table 1. Present and future implementation of sensing technologies in viticulture

Vinicultural application	Key opportunities	Key challenges
Evaluation of soil characteristics and quality	• Retain soil quality and prevent soil pollution	•Implementation of low-cost DSM technique • Temporal precision

	• Properly detect and track soil variation at a lower cost • Evaluate Soil organic carbon (SOC) and soil total nitrogen (STN) accumulation and dynamical variations	• Time frequency of data • Accurate temporal distribution prediction
Foliage architecture, vegetative development, and nutritional state	• Enhance fruit microclimate by enhanced canopy management procedures • Minimize input costs (e.g. fertilizer, fungicides, water) • Create diagnostic tools that are physiologically aligned	•High variation within vineyard development • Dense canopies • Canopy separation • Artificial intelligence restrictions
Identification and management of pests and diseases	• Enhance pest and disease monitoring and management • Offer early warnings regarding pest and disease problems • Limit the usage of insecticides and pesticides	• Inadequate equipment to examine the whole canopy and provide therapy right away (if required) • Symptoms that are similar among infections and/or illnesses
Vine water status	• Recognize the signs and symptoms of water stress • Increase the effectiveness with which water is used • Conserve energy	• Establishing stress thresholds at various degrees of stress • Observing frequency over time
Crop predictions and yield attributes	• Enhance winery logistics and lower risks and expenses associated with wine production	• Identifying the relevant clusters • High variance • Obstruction issues
Fruit composition and qualities	• Have a better knowledge of the composition of fruits before harvesting	• Data resulting mainly from the skin rather than the pulp • Includes only a few fruit chemicals • Fruit must be apparent
Sample selection from vineyards	• Make all vineyard sample tasks more accurate (e.g. maturity, yield, nutrition)	• Field testing and huge datasets are still required
Targeted management	• Achieve sustainable assessment while reducing expenses through smart input application on the go	• Needs floating rate application technique • Environmental impact standards must be devised
Careful harvesting	• Increase the quality of wine and the items used in wineries • Develop wines with certain wine profiles in mind	• Machines with on-board bins or supplementary bins pulled by chaser tractors are required • Selective harvesting machinery is not required

Several different techniques can be applied to improve wine production and minimize the possible environmental impacts in the viticulture industry. Some of the techniques are listed below.

1. Spectroscopy

Spectrometers can measure spectral reflectance. The VIS (400–750 nm) and NIR (750–2500 nm) spectral wavelengths are essential in agricultural production systems since they have numerous applications. Many organic compounds undergo electronic transitions in the visible range, altering characteristics such as colour. As a result, this spectral region is frequently employed to evaluate pigments in grapevine leaves and fruit. Soil characteristics can also be assessed using spectroscopy-based technology (Schirrmann, Gebbers, & Kramer, 2013).

2. Multispectral imaging

Unlike traditional spectroscopy, which records the reaction of small spot size to a continuous spectrum, MSI monitors radiation in a small number of short frequencies, usually four or six (e.g. RGB and NIR). Filters or instruments that are sensitive to specific frequencies can be used to separate wavelengths. Spectral indicators are generally associated with photosynthetically active biomass in agricultural production, which might be linked to plants' size and/or health. The NDVI and PCD indicators are the most extensively used spectral indicators in viticulture (Hall, Lamb, Holzapfel, & Louis, 2011). Several researches have evaluated the uses of remote sensing vegetation indicators in viticulture (Giovos, Tassopoulos, Kalivas, Lougkos, & Priovolou, 2021; Matese & Di Gennaro, 2021).

3. Hyperspectral imaging

Hyperspectral imaging (HIS) is also a useful tool for assessing foods and crops (Y. Liu, Pu, & Sun, 2017). The fundamental difference between HIS and MSI is spectral resolution. HSI generates the spectra of all pixels of an item by dealing with smaller wavelengths throughout a continuous spectral range. HIS sensors gather data in the form of a series of 'pictures,' each of which represents a certain wavelength range of the electromagnetic spectrum (Grahn & Geladi, 2007). The major benefit of HSI over MSI is that the user does not need previous item information because a whole spectrum is acquired at each geographic place. The fundamental drawback of HIS against MSI is expense and complexity; however, rapid technological advancements are projected to alleviate this restriction with the development of faster processors, more delicate sensors, and larger data storage devices. Because HSI is still a relatively new approach, its full potential has yet to be exploited. New technologies such as deep learning are being tested (Paoletti, Haut, Plaza, & Plaza, 2019).

4. Chlorophyll fluorescence

Different paths determine the technology's premise that light energy received by Chlorine molecules in living plant tissues can take. The Chlorine fluorescence screening method, which is centered on the output characteristic of UV-absorbing phenolic content in leaf epidermises and fruit skins screening under laying Chlorine, has become especially helpful in agriculture as a method to observe dietary factors and dyes (Agati et al., 2013). Portable sensors that may be utilized manually or attached to moving vehicles have expanded the technique to field research.

5. Thermography

Another technique with opportunities for agricultural uses is infrared thermography. Thermography has mostly been used to regulate the water condition of plants. The use of thermographic methods is based on the fact that as water is lost through stomata, the temperature of the leaf drops. When stomata are closed, transpiration ceases, and leaf temperature rises. Leaf temperature is connected to stomatal conductance when external conditions are constant; hence canopy temperature has long been recognized as an indicator of plant water. On the other hand, changing climatic circumstances have an impact on crop canopy temperature (Maes & Steppe, 2012). Thermal stress indicators such as the Crop Water Stress Index (CWSI) and the infrared thermography (Ig) have been created to compensate for the influence of environmental changes on canopy temperature.

6. LiDAR

LiDAR is a measuring method that uses pulsed laser beams to illuminate an object and a sensor to detect the scattered waves. The target can then be digitally 3-D reconstructed using different laser return timings and frequencies. LiDAR, also known as laser scanning or 3-D scanning, has been used on the ground, air, and mobile devices. LiDAR can offer information across broad areas when used from the air (Maes & Steppe, 2012). It may be mounted on ground-based vehicles and used to measure plant traits and architecture.

7. Computer vision

Computer vision (CV) is described as a system that captures, analyzes, evaluates, and separates data from photographs in order to offer numerical or symbolic information, such as the assessment or forecasting of significant attributes of the selected object, in a quick, contactless, repeatable, and precise way (Grimm et al., 2019). CV is a set of AI techniques whose goal is to enable a system to 'interpret' an image, or more accurately, to 'build clear, coherent descriptors of physical objects from photographs'. CV provides an automated method for assessing the qualities of a target object in a quick, contactless, consistent, and precise manner (Blasco, Aleixos, & Moltó, 2003). Fault recognition, colour prediction, shape and size assessment are only a few aspects for which image analysis can offer a valid and accurate evaluation (Cubero, Aleixos, Moltó, Gómez-Sanchis, & Blasco, 2011).

8. Robots

Robots are ground-based systems that have the ability to transform all types of agricultural systems, particularly viticulture (Fountas, Mylonas, et al., 2020; Saiz-Rubio & Rovira-Más, 2020; Vougioukas, 2019). LiDAR scanners are rapidly employed as guidance, vehicle speed, and security sensors in automation and robots. These robots are expected to meet all safety requirements, have stable autonomous navigation, and display the needed capacity for precise all-terrain operations. GRAPE is a robot that distributes pheromone dispensers on its own. Harvesting is another viticulture task that will be mechanized thanks to Bacchus and other prototypes being developed around the world (Vrochidou et al., 2021).

AI may be quite beneficial since it can translate data into various bits of information that grape growers can use to make informed decisions. Even at small sizes, all of the sensing techniques and platforms outlined earlier combine to provide a high data collecting competence for today's grape producer. Nevertheless, consistent research advancement will be required. Many additional uses and developments must be explored to understand better how to model the crop into accurate statistics and extract more information. Furthermore, while this information is important to grape producers for farming methods, it has both direct and indirect environmental uses since crop data offers accurate management of ecologically crucial resources like water and soil.

Machine learning (ML) is the most popular discipline for automating knowledge in agriculture, particularly viticulture (Cai et al., 2019; Fuentes et al., 2018). ML is at the heart of AI, and it's defined as the study of getting computers to learn on their own, in most circumstances so that they can turn data into meaningful information (Jordan & Mitchell, 2015). As a result, by combining machine learning with the wide number of data collecting choices already accessible, grape growers and winemakers can deploy data-driven solutions to improve and optimize their production processes. This is accomplished through training, which entails the creation of mathematical models that are fed by data. In the case of machine learning, there are numerous processes involved.

The first stage is gathering data and organizing it into a collection of samples (X, or independent variable in statistical language), each of which contains two or more variables (xi, or features or attributes) that define some aspect of the samples. In order to find any correlations between X and y, each sample is linked to a parameter of interest (y, dependent variable, also called as the standard variable). The approach is known as supervised learning when all samples are labeled. Semi-supervised learning is the method of training without labels on some data (Jordan & Mitchell, 2015). For example, when utilizing spectroscopy, the complete spectrum can be discretized into equally spaced variables due to specific frequencies, spatial frequency indices or major components (Jordan & Mitchell, 2015). CV feeds the algorithms the matrices that describe the images (using the three common colour components or one channel). Hyperspectral imaging, which combines imaging and spectroscopy, can be employed in both dimensions (Bendel et al., 2020).

After all of the data has been properly formatted and treated, the following stage is to train the models that are at the heart of machine learning (i.e., training models using algorithms fed by data). The most difficult phase, and the one that necessitates user experience, is model training. This is because it is vital to understand the many algorithms that can be employed, their benefits and drawbacks, and the best option for the data available. Many machine learning methods have been used in viticulture to achieve various goals. Such as SVMs for detection of diseases, grape varieties classification, and yield forecasting, an optimal algorithm for disease identification using imagery, deep learning for image classification in vineyards and hyperspectral data evaluation for disease detection (Bendel et al., 2020). Different deep learning methods, including convolutional neural networks (Barré et al., 2019; Hsieh & Kiang, 2020), autoencoders(Karim et al., 2020; Yu, Lu, & Liu, 2018), and recurrent neural networks (Chen, Xiao, Zhang, Xie, & Wang, 2020; L.-W. Liu, Hsieh, Lin, Wang, & Lin, 2021; Mouatadid, Adamowski, Tiwari, & Quilty, 2019), have been employed to construct advanced models for precision agriculture.

After a model has been tweaked, trained, and verified, it can be utilized for additional purposes. Such as, in digital viticulture, this would imply combining a sensor and a system with the trained model incorporated. The model would acquire a steady stream of data from the sensor and generate predictions grounded on the learned directions and relations. However, because this is also a data-gathering procedure, it is feasible to take benefit of this and repeat the process using the freshly collected data. It's vital to remember that a model's output isn't the goal but rather a tool for making better judgments.

3 Conclusion

This article presents a complete analysis of various digital non-invasive techniques in the grape and wine industry that are either in progress or are now in use. To address present and future concerns such as climate change, the environment, waste, labour shortages, and rising production costs, one must enhance resource use effectiveness in all agricultural systems. The application of various proximal and remote sensing technologies has enhanced the knowledge of vineyard variation in terms of geographical disparities and sequential dynamics and the underlying reasons for such variation. The study shows how knowing this information allows grape growers and winemakers to use inputs more effectively through specific applications and harvest fruit packages strategically based on yield and/or fruit quality requirements and product requirements. Reduced input costs, higher efficiencies, and a better end product are all economic benefits of each of these outcomes. It's challenging to show that precise and digital viticulture and associated technology improve the environment. There are no reported examples from the grape and wine industries till today. Nevertheless, given the rising control of chemical usage in agriculture and the continued commercialization of machinery equipped with VRA technology and sensors to quantify canopy size, environmental benefits are unavoidable.

One of the main goals of digital viticulture is to provide grape growers and winemakers with precise data, pictures, and maps in real-time to help them manage their vineyards more efficiently and sustainably. Even though many digital apps are currently accessible, the rapid and accurate analysis and interpretation of data that is required for immediate adoption necessitate monitoring and integration at the vineyard. Since smart sensing techniques have an immense opportunity for producers at all stages, their implementation and regular use will be centered on accessible operating system and devices and the cost of integrating decision-support systems on a field scale. IoT, data science, AI, and automation can all assist producers in overcoming obstacles in the vineyard. Data rights and security, especially when data is obtained through third parties, is a problem that must be addressed in the coming years to enable the widespread adoption of such technology.

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