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Review article

How can proximal sensors help decision-making in grape production?

Tamás Mizik

Department of Agricultural Economics, Institute of Sustainable Development, Corvinus University of Budapest, Budapest, Hungary

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ABSTRACT

Precision viticulture (PV) aims at achieving greater profit in a more sustainable way through improved resource use efficiency and greater production. PV is based on reliable data provided by different sensors. This study aims to identify the role of proximal sensors in the decision support of PV. During the selection process, 53 of 366 articles identified were relevant for the study. These articles are classified into four groups: management zone delineation (27 articles), disease/pest prevention (11 articles), water management (11 articles), and better grape quality (5 articles). Differentiation between heterogeneous management zones is the basis for site-specific actions. The most important data that sensors provide for this are climatic and soil information. This makes it possible to predict harvesting time or identify areas for plantations. The recognition and prevention of diseases/pests are of crucial importance. Combined platforms/systems provide a good option without any compatibility problems, while variable rate spraying makes pesticide use much lower. Vine water status is the key to water management. Soil moisture and weather data can provide good insight; however, leaf water potential and canopy temperature are also used for better measurement. Although vine irrigation systems are expensive, the price premium of high-quality berries compensates for this because grape quality is closely related to its price.

1. Introduction

The continuously increasing global population is one of the greatest challenges of humanity. As available resources, especially land, are limited, more efficient production is of key importance. One of the promising answers is precision agriculture. The International Society for Precision Agriculture formulated a widely accepted definition of precision agriculture which is the following: "Precision Agriculture is a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production." [1]. Among others, this definition draws attention to the importance of data in decision making support. Sensors provide primary information on many elements of the production process; however, interactions with farmers must also be considered.

Precision farming contains different, interconnected elements to achieve higher yields through input and process optimizations. This includes the collection of a wide range of production-related data, their proper processing, and, finally, the decision-making and implementation based on the collected and processed data (Fig. 1.). The arrow around the circle represents the continuity of the process, as the actions implemented impact the different production factors; therefore, data should be collected and processed again to reflect changing circumstances.

E-mail address: tamas.mizik@uni-corvinus.hu.

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Data collection covers different soil parameters (e.g., quality, fertility, nutrient profile, water absorption capacity, weed density), as well as weather parameters (e.g., rainfall, temperature), which making it possible to construct a site-specific analysis [2]. Its providers are the different on-site sensors, satellites, and other data sources. In general, sensors can be classified into two categories: proximal and remote sensors. Remote sensors can be used at a distance, while proximal sensors are close to plants or soil [3]. This article applies this narrow interpretation of proximal sensors. Although different image-based technologies supported by artificial intelligence are becoming more popular, they are mostly based on imaging tools (remote sensors) rather than proximal sensors.

Data processing deals with an enormous amount of data by combining them into input to support the decision-making process. This process includes information technology, different software, and hardware elements. Only properly processed data sets can provide site-specific results (soil, plant, and/or animal characteristics). This makes differentiated/variable input use possible, in accordance with the actual needs of the technology concerned. Fig. 2 provides an overview of different categories of precision agriculture technologies (hereinafter referred to as PATs). These categories are directly linked to the different parts of Fig. 1. Recording technologies are responsible for data collection, transforming technologies refer to data processing, while guidance and reacting technologies are related to decision making and implementation using different PATs that make differentiated input allocation possible.

Viticulture is not the most important agricultural sector in terms of production area, as the grape area represents only 0.15% of the world's total agricultural land without forests (Author's calculation based on (Author's calculation based on [5,6]). However, grapes are the most important fruit in terms of area and production, as they cover 10.72% of the total land of fruits and 8.80% of production (Author's calculation based on [4]). Moreover, it should also be noted that most grapes are used for wine production, providing a higher value added compared to the other fruit products. Nevertheless, the limited available land also applies to this sector; therefore, PATs are important for efficient and optimized production in precision viticulture (hereinafter referred to as PV). PV also aims to reduce the environmental impacts of production, for example, resulting in lower CO_2 emissions and greater water efficiency, while higher investment costs are generally covered by higher revenues [7]. The main sources of higher revenues are higher and more stable yields and better grape quality. Targeted management not only improves grape yield and quality, but also improves the quality of areas with poorer soil quality [8]. Combining different management and production tools (for example, organic or biodynamic viticulture) may provide even further benefits [9]. For example, the application of PV can significantly reduce greenhouse gas emissions [10]. However, environmental benefits are generally easier to quantify compared with economic benefits [11].

Similarly to precision agriculture, data are also a key element in PV. Sensors provide essential data on different aspects of vine production, such as soil characteristics, agroclimatic conditions, canopy and grape attributes, etc. By proper processing of this huge amount of data, different management zones can be set up and site-specific interventions become possible. Furthermore, due to their wireless nature, this information can be received by different mobile devices, such as mobile phones. The widespread use of mobile devices and the Internet provide a simple opportunity to increase the adoption of PV, as there is no technological barrier in the use of mobile phones [12]. Sensors can monitor weather, soil, or grape conditions to forecast the location and time of site-specific intervention [13]. Data collected and processed provide the basis for the optimization of production strategies, increased energy efficiency or the reduction of production risks [14]. This contributes to higher yields and better product quality, while resulting in a lower environmental impact. Based on the results of Ammoniaci et al. [15], proximal sensors provide information quickly and at a low cost, among others, for soil management, stress, and ripening assessment. Both contribute to higher profitability (lower production costs, higher yield, and product quality) and provide the opportunity for immediate interventions in the case of any unexpected events. They also highlighted that full decision support systems are expensive and their use requires high operational knowledge.

However, potential compatibility problems of different networks and platforms should also be taken into account [16].

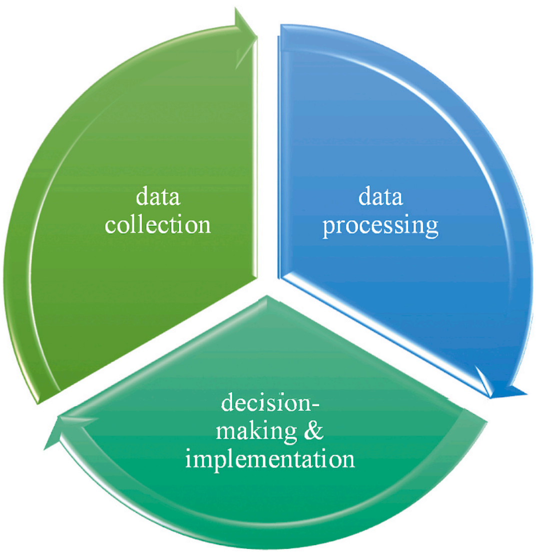

Fig. 1. Schematic interpretation of the precision agriculture workflow.

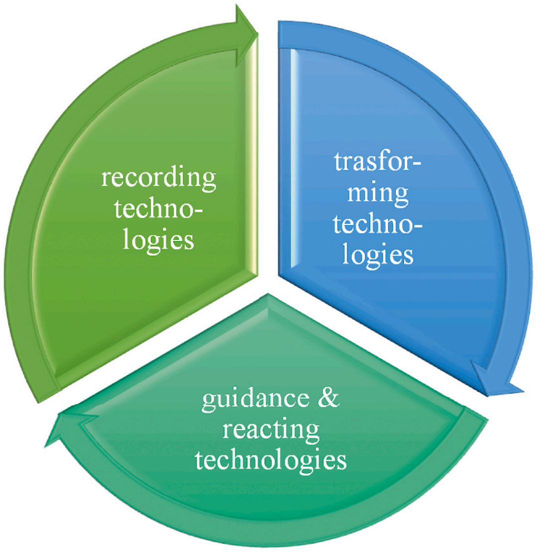

Fig. 2. Categories of precision agriculture technologies. Author's elaboration based on [4].

Furthermore, it should always be kept in mind that these data are continuously collected and stored somewhere, which can be vulnerable to several threats; therefore, secure systems, such as modular blockchain solutions, are of high importance [17]. Tardaguila et al. [18] provide a detailed overview of the current and future application of digital technologies, as well as non-invasive sensing technologies related to forecasting diseases/pathogens in vineyards. As they highlighted, improved resource use efficiency is essential not only for the future, but also for current challenges and PV can provide this solution. However, complex PV systems can be expensive; especially variable cost (depreciation and water use) can be high in the case of irrigation [19].

2. Materials and methods

This study aims to identify the role of proximal sensors in the decision support of precision viticulture; therefore, ScienceDirect and Web of Science were screened for relevant articles. Other sources, such as Scopus, JSTOR, and AgEcon Search, were also checked; however, they have not provided additional articles. The last searching operation was carried out on January 11, 2023. Table 1 Provides details of keywords and Boolean operators of the article selection process.

The initial screening resulted in 69 and 485 items on ScienceDirect and Web of Science, respectively. To have more reliable results, these items were limited to scientific (peer reviewed) and review articles and were filtered to English in each database. This resulted in 424 articles. The duplicates were then removed. This process provided 366 studies for screening against title and abstract. Due to the lack of proximal sensors, for example, only (aerial) imaging tools were used and combined with different models or grape production was not part of the analysis, 284 articles were excluded. As the article applies the narrow interpretation of proximal sensors, all scientific items dealing only with remote sensors are excluded from this analysis. During in-depth screening, 28 more articles were removed because they focused only on technology, e.g., network compatibility, concentrated only on methodological issues, and lacked field data collection, e.g., tags or QR codes. In terms of the entire selection process, the PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was applied [20]. Fig. 3 Provides an overview of the article selection process.

Regarding the composition of the relevant articles, eight were published in 2022, seven in 2018, six in 2021, and five in 2013 and 2011. In the other years, there were four or fewer articles relevant for the review. Regarding the place of publications, the Australian Journal of Grape and Wine Research was the most frequent place with 7 articles, followed by Computers and Electronics in Agriculture (6 articles), Precision Agriculture (6 articles), Biosystems Engineering (4 articles) and Sensors (4 articles). The remaining 26 articles were published in 19 different journals.

Table 1
Keywords and Boolean operators of the article selection process.

precision viticulture OR precision viniculture	AND	sensor*	AND	decision support

Note: * as a wildcard was added to the word "sensor" in the queries when it was possible.

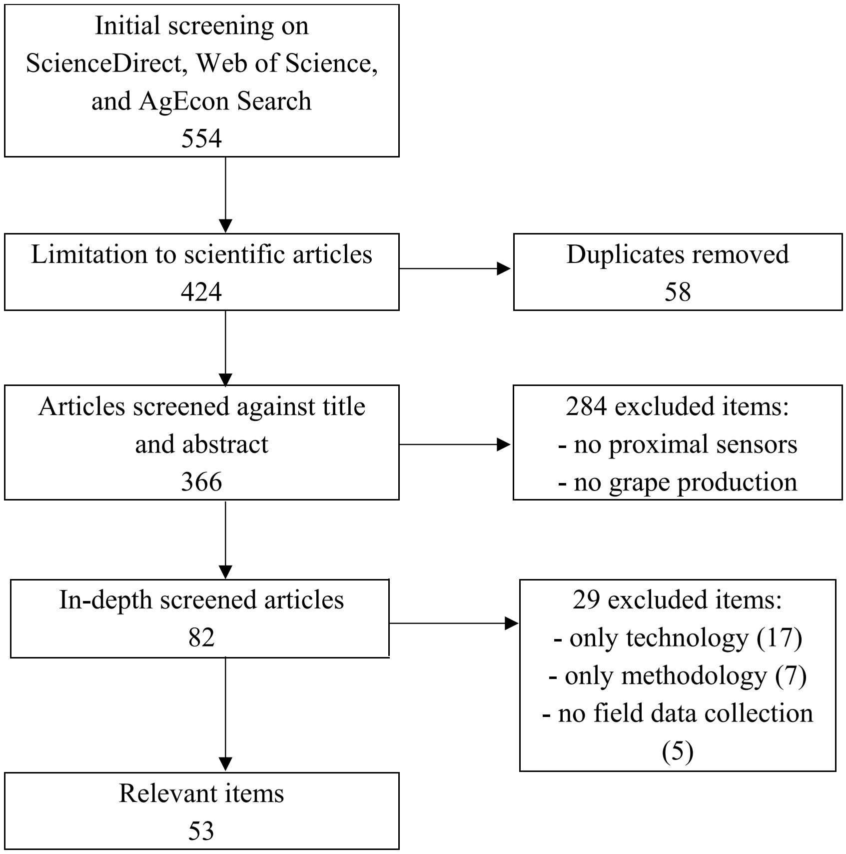

Fig. 3. Overview of the article selection process.

3. Results

Sensors provide data for the processing stage to support the decision-making process. The processed data can be used for multiple purposes, most notably for setting up homogenous management zones. The basis of any kind of site-specific intervention is the delineation of the different management zones of the vineyard. This aims at disease/pest prevention or proper water status. Significant savings can be achieved with timely interventions. The delineation process relies mainly on the soil characteristics that are reflected in the canopy structure. Another relevant area of decision-support is water management, which will become more important due to global warming. Furthermore, sensor-provided data can be used for yield and quality management.

The rest of this section follows the order of the areas above. First, the role of proximal sensors in the delineation of management zones is presented (3.1.). This is followed by an analysis on how proximal sensors can support disease/pest prevention (3.2.). The third subsection provides information on how proximal sensors can contribute to water management (3.3.). Finally, the results of the articles on how proximal sensors can enhance grape quality are presented (3.4.).

3.1. Proximal sensors for management zone delineation

Anastasiou et al. [21] applied multivariate geostatistical techniques to combine spatial and temporal data from a multi-band radiometer and a geophysical sensor to form homogeneous vineyard zones. Using different geostatistical methods, the results turned out to be useful for site-specific management. Morari et al. [22] also applied a multivariate geostatistical technique based on data from electromagnetic induction scans and electrical resistivity tomography to delineate zones within the vineyard. They found a connection between electrical conductivity and soil physical properties, making delineation possible in a relatively inexpensive way. This is of utmost importance in PV. Estevez et al. [23] suggested the combination of different methods because not all tools are suitable to delineate all types of soil. In their experiment, electromagnetic induction (EMI) sensor-based information and the normalized difference vegetation index together proved to be more effective and beneficial than any of them alone. Martini et al. [24] also provided evidence on how EMI sensors are suitable for delineation.

Based on color and texture, Abdelghafour et al. [25] set up a pixel-wise classification to identify different phenological stages of the grapevine canopy. An ultrasonic sensor was used to properly measure distances. Euclidean vectors, multivariate Gaussian models, and Bayesian maximum a posteriori probability estimation were used and supported by two vector representation models to increase the quality of the results. The overall accuracy of this system in the detection of spatial differences was reasonably high, between 88 and 93%. Trought and Bramley [26] studied vineyard variability based on remote and proximal sensing data to find canopy plant cell density, trunk circumference, and apparent electrical conductivity of the soil. The results can contribute to better timing for even a site-specific harvest. The main advantage of characterizing spatial and temporal changes in the vineyard is to help producers make decisions during their busiest period of the year. The anthocyanin content of grapes can also be used to reveal spatial differences. Baluja et al. [27,28] measured this with fluorescence-based proximal sensors and their estimated data were highly correlated with the real anthocyanin content in the berries. Bramley et al. [29] applied the same technology and received similar results in South Australia. Using sensory and wine chemistry data together provides even more reliable information to separate different management zones ([30, 31]). Fluorescence sensors can provide data on the chlorophyll, flavonol, and nitrogen concentrations of leaves (vegetative status), which can also be used to separate different management zones ([32]).

Weather, microclimate, soil, and vegetation data are important elements of zone differentiation, and some of them can only be collected from the site (microclimate, soil, and vegetation). By processing them, Pereyra et al. [11] set up different vigour zones that made site-specific actions (for example, fertilization and irrigation) possible. The normalized difference vegetation index (NDVI) can be calculated to identify spatial differences based on data from apparent electrical conductivity (EC_a) and electromagnetic induction sensors ([33]). Priori et al. [33] compared wines from these identified zones and found high differences in terms of quality (e.g., dry extract, color intensity). Knowing this can help produce better quality wines. Tagarakis et al. [34] also used an EC_a sensor together with a crop circle sensor that emits amber and near infrared wavelengths. The latter was used to calculate the NDVI. By applying NDVI and fuzzy clustering, they provided a simplified method for delineation and set up homogeneous management zones in 2 years. Implementing an infrared laser scanner (LiDAR) into this system could make delineation even more precise ([35]). Combining different sensing technologies (for example reflectometry sensors, NDVI, EC_a, carbon isotope ratio analysis, and bunch number) always provides more reliable results ([36–38]).

Matese et al. [39] set up a customizable system based on micrometeorological sensors to support decision making in the vineyards. This made the development of different management zones possible. Additionally, processed data can help to evaluate new areas for plantations. This system outperformed commercial systems in terms of flexibility, functionality, and efficiency. The electrical resistivity of the soil measured by the resistivity meter is also a proper method of delineation ([40,41]). Using a handheld fluorescence sensor, Rey-Caramés et al. [42] applied geostatistical analysis to model the chlorophyll and nitrogen content of leaves. Additionally, shoot pruning weight was also taken into account. They were able to reveal spatio-temporal differences, which are the basis of PV, such as variable rate input use. One of their remarkable results was that it is more efficient if the management zones are bounded first before data processing. The leaf area index is also an important tool for identifying the spatial variability of the vine. Arnó et al. [43] used a LiDAR sensor and highlighted that the scanned length should be properly chosen; otherwise, spatial differences will be masked. Optical sensors based on chlorophyll fluorescence can provide information on N uptake, which is the basis for the variable rate of N use ([44]). The water status of the plant is also a well-known indicator of the management zone delineation. Among other tools and technologies, Yu and Kurtural [45] used an electrical conductivity sensor that turned out to be an effective tool to estimate this status.

It should be noted that data collection and data processing levels are quite different in terms of devices, prices, and expectations. Peres et al. [46] identified this gap between data collecting tools and data processing devices. The former is generally cheaper and contains many small items; the latter provides higher level data needed for decision making. Computing power can be costly increased; however, even in that case only a limited amount of data can potentially be processed. The authors proposed the Intelligent Precision Agriculture Gateway (iPAGAT) as an intermediate data processing layer between these two end points, and data can be easily displayed on authenticated smartphones to support site-specific actions.

Regarding the different ways in which the proximal sensors support the management zone delineation, Table 2 Provides an overview of the related literature.

3.2. Proximal sensors supporting disease/pest prevention

Early prevention is of utmost importance. It provides the opportunity to prevent further spread of diseases or pests at a relatively inexpensive cost (targeted intervention). It should also be noted that zone delineation tools can often be used for disease/pest prevention too [25].

Daglio et al. [47] used optical sensors for the early detection of different diseases. This is a low-cost technology. However, further improvement in data processing is needed to reduce the time required for visual control. A well-timed intervention reduces costs and limits the spread of the different diseases. Based on the data of ultrasonic sensors attached to the sprayer to measure the variations in

Table 2
Summary of how proximal sensors can support the management zone delineation.

Type of sensors	Data processing methods	Supporting literature
electrical resistivity, electro-magnetic induction, apparent electrical conductivity, resistivity meter, infrared laser scanner, fluorescence, tomography, geophysical, micrometeorological, ultrasonic, crop circle	Bayesian estimation, Gaussian models, Euclidean vectors, multivariate geostatistical techniques, stepwise linear diagonal discriminant analysis, linear regression, principal component analysis, fuzzy clustering, normalized difference vegetation index, carbon isotope ratio analysis	[11,21–46]

crop width, Gil et al. [48] optimized the use of pesticides. The volume rate based on tree row volume instead of on the size of the area resulted in 57% savings on average in terms of quantity due to the real time adjustment of the flow rate. Continuing this work, Llorens et al. [49] compared the conventional spraying method based on the size of the area with a spraying application with variable rate. The latter sprayer was equipped with ultrasonic sensors to be able to adjust the emitted flow rate based on real time information on the canopy volume. According to their results, 58% savings can be achieved with variable rate technology on average without significant leaf differences. The leaf area index is also a commonly used tool for various spraying. Del-Moral-Martínez et al. [50] applied a terrestrial laser scanner to measure it and successfully applied this method for optimized dosing. Gatti et al. [51] proposed a terrestrial multi-sensor that integrates microclimate (for example humidity and air temperature) and imaging sensors. With a built-in algorithm, it provided a satisfactory estimate of the Canopy Index (CI). The use of CI maps makes variable rate spraying possible. LiDAR sensors can also support savings on pesticide use (early or targeted treatment) by providing information on the canopy ([52,53]).

Pérez-Expósito et al. [54] presented a complex system called VineSens that supports the decision-making process. This covers hardware and software; therefore, data collection and processing. The data collected include temperature, rainfall, and humidity/moisture. By using a predictive model, the system can forecast downy mildew and alert users on their mobile devices. Timely and site-specific interventions reduce the cost of plant protection; thus, they decrease the overall environmental impact and contribute to a higher quality of grapes. Morais et al. [55] tested a platform called MPWiNodeZ that can recharge its batteries in three different ways, i.e., with wind, hydro, and solar energy. The self-sustaining characteristic of this device makes it possible to build up a forecasting model for grapevine powdery mildew. In Kleb et al.'s [56] experiment, proximal sensors measured temperature, relative humidity, and leaf wetness. On the basis of those data, they were able to provide more precise data compared to weather station data, which can make the control of downy mildew faster and more efficient, and therefore cheaper. Table 3 Provides an overview of the articles analyzed in this subsection.

3.3. Proximal sensors for water management

Climate change along with global warming and water scarcity calls for a more efficient use of this resource. Therefore, the water management for any irrigation system should be based on the needs of the vineyard that may have significant spatial variability. According to Anastasiou et al. [57], the vine water status was the most important factor in estimating the volume of grapes. Pre-harvest data can be well used to forecast the post-harvest characteristics of grapes. The potential water deficit, which is strongly correlated with yields and quality, can be estimated by using different indices. Serrano and Gorchs [58] proposed the combined use of the photochemical reflectance index, the NDVI, and the water index. They collected data with a ceptometer and a spectroradiometer and applied principal component analysis.

Kotsaki et al. [59] tested an optical sensor with a silicon photodiode sensor (GreenSeeker) that provided reliable data on the status of the vine water. This technology had many advantages; for example, it can be used parallelly with other vineyard operations and it is not restricted by any weather conditions. GreenSeeker provides data comparable to multispectral image analysis ([60,61]). Fernandez-Novales et al. [62] used proximal near-infrared spectroscopy to differentiate the water status of the vineyards for precision irrigation. By applying a partial least squares (PLS) model, this method classified the different areas with high reliability as the determination coefficients ranged from 86 to 90%. In their other study, Fernández-Novales et al. [63] used a ground robot called VineScout. It was equipped with thermal infrared radiometry to determine the water status of the vineyards. This process is based on leaf water potential and the temperature of the grapevine canopy, while the PLS was applied for data processing. This technology can also provide data for delineation; therefore, it makes precision water management possible. However, the determination coefficients of the prediction were much lower than those of proximal near-infrared spectroscopy. Diago et al. [64] collected data with near infrared spectroscopy. Their regression models provided a good estimation of water status; therefore, they proved to be suitable to support precision irrigation.

García-Tejero et al. [65] used thermography to monitor the water status of grapevines based on the temperature of the canopy. This simple and non-normalized method performed the best among the different thermal indicators and was suitable to support water management. They also identified the best time for thermal data collection, between 11 and 14 h (local time), as all climate-related data were collected hourly. Cancela et al. [66] used a soil electrical conductivity meter with random forest regression models which proved to be effective in water management at a relatively low cost. The main advantage of this method is its generalizability, i.e., it can be applied to other crops. Electrical resistivity tomography can also be used to estimate soil water availability; therefore, it provides good opportunities for water management ([67]).

Finco et al. [19] proposed an innovative software platform (Smart Vitis) based on remote and proximal sensors that can be used to monitor the water status of the vine. This can be a good tool for handling spatial and temporal differences; therefore, it contributes to optimizing irrigation. Zhou et al. [68] installed a thermal imaging sensor and a digital camera to collect data on the canopy. Furthermore, an AgWeatherNet station was used to obtain weather-related data, while a thermal sensor provided data on canopy temperatures. The purpose of this method was to help water management by providing a real-time assessment of the water status of

Table 3
Summary of how proximal sensors can support disease/pest prevention.

Type of sensors	Data processing methods	Supporting literature
MPWiNodeZ (platform), optical, ultrasonic, VineSens (system), terrestrial laser, infrared laser scanner	predictive model	[25,47–56]

grapevine. Table 4 Summarizes the major elements of the analyzed articles.

3.4. Proximal sensors for better grape quality

A site-specific NDVI based on data provided by infrared canopy sensors makes optimized berry harvest possible ([69]). This is crucial for better grape quality. Better grape quality results in higher producer price and better quality of the final products, for example, raisin or wine; therefore, this is an important aim of every vine grower. Anastasiou et al. [70] found that weather and soil conditions significantly impact the quantity and quality of grapes; however, the former proved to be more important, while the latter influenced the quantity of grapes more than its quality. It should be noted that proper cultivation practices help minimize these impacts. Altherwy and McCann [71] collected data on the moisture content with radio frequency signals. Based on these data, their regression model achieved 90% accuracy; therefore, it can provide information on grape yields and health in a low-cost and contactless way. Karimi et al. [72] applied agrometeorological sensors to optimize grape production. Proper data processing and interpretation allow for the scheduling of site-specific interventions such as irrigation, prevention of fungal diseases or sun burning damage, and harvesting time. This has a significant impact on the quality of the grapes.

Costa et al. [73] used a spectroradiometer and different mathematical models to predict the attributes of grape quality and maturation stage. Their models provided high accuracy, 70–90% for certain contents (soluble solids, anthocyanins, and flavonoids), and 93% for the maturation stages of the vines. Evaluating these attributes significantly helps to use site-specific measures to achieve better grape quality. Table 5 Highlights the major elements of the literature on how proximal sensors can contribute to better grape quality.

4. Discussion and conclusions

The aim of this literature review was to provide an overview on how proximal sensors can be used to support decision-making in PV. Of the 366 selected articles, 82 were in-depth screened and only 53 turned out to be relevant for this study. The major reason for the exclusion was the lack of sensors, because those articles dealt only with (aerial) imaging tools.

Due to many factors, most notably climate change, rapidly increasing input prices, and high demand for quality products, PV is becoming more popular around the world. This is further emphasized by the fact that grape is one of the most popular fruits worldwide [74]. However, site experiments of most of the relevant articles were conducted in the so-called old world wine producing countries. As can be seen in Fig. 4., 39 of the 53 country-specific articles were related to those countries, while only 14 were in the new world wine producing countries.

The relevant articles were classified into four themes: management zone delineation, disease/pest prevention, water management, and better grape quality. It should be highlighted that these are not completely separated areas because they are closely linked to each other. Most site-specific actions are based on management zone delineation, disease/pest prevention, and water management contribute to better grape quality (see e.g. Ref. [25]). Fig. 5 Provides a graphical representation of the four identified themes.

PV can only be effective if the right quantity and quality of data are available and are properly processed and interpreted. Although machine learning and artificial intelligence are rapidly evolving [75], the role of the human factor in the decision-making process is still significant. The quality of wine particularly depends on the human factor [76]. On the basis of relevant and properly processed data, all the above decision-making areas can be supported.

Differentiation between heterogeneous management zones is the basis for site-specific actions, notably soil management, plant characteristics, and product quality and quantity. The most important data that sensors provide for this are climatic and soil information. Based on this information, not only can the right harvest timing be forecast, but also can areas for plantations be identified. Knowing the different phenological stages of the grapevine canopy is also a useful tool to detect spatial differences. As the amount of data increases significantly by the number of sensors, reducing the workload of the processing stage with an intermediate data processing layer can be a good option. This subtopic has the largest number of articles, 27 out of the total 53. It is not surprising, since the management zone delineation is the basis for most site-specific actions, such as fertilizing, spraying, and irrigation. Additionally, proper site-specific management can contribute to higher yields and better grape quality.

Disease/pest recognition and prevention can never be too early, as they can save significant costs. In this case, early alerting tools and data visualization are important. Complex platforms/systems provide a good option without any potential compatibility problems. In terms of intervention, variable rate spraying applications make pesticide use much lower as they can adjust the emitted flow rate based on real time information.

Any water management action should be based on the vine water status. In addition to data on soil moisture and weather (temperature and rainfall), leaf water potential and grapevine canopy temperature are used to identify this. Proper timing of the data

Table 4
Summary of how proximal sensors can support water management.

Type of sensors	Data processing methods	Supporting literature
GreenSeeker (combined sensor technology), soil electrical conductivity, electrical resistivity tomography, near infrared spectroscopy, thermal imaging, ceptometer, spectroradiometer	non-normalized method, partial least squares, random forest regression, principal component analysis, correlation analysis	[19,57–68]

Table 5
Summary of how proximal sensors can support better grape quality.

Type of sensors	Data processing methods	Supporting literature
agrometeorological, proximal, spectroradiometer, radio frequency signals	mathematical models, normalized difference vegetation index	[69–73]

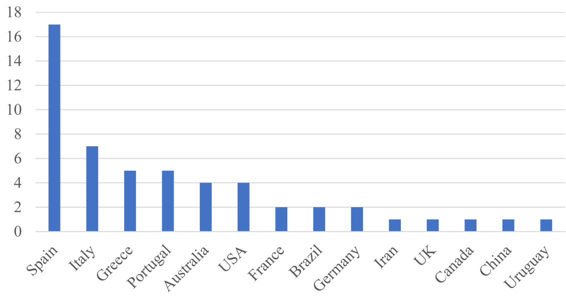

Fig. 4. Geographical composition of the selected articles.

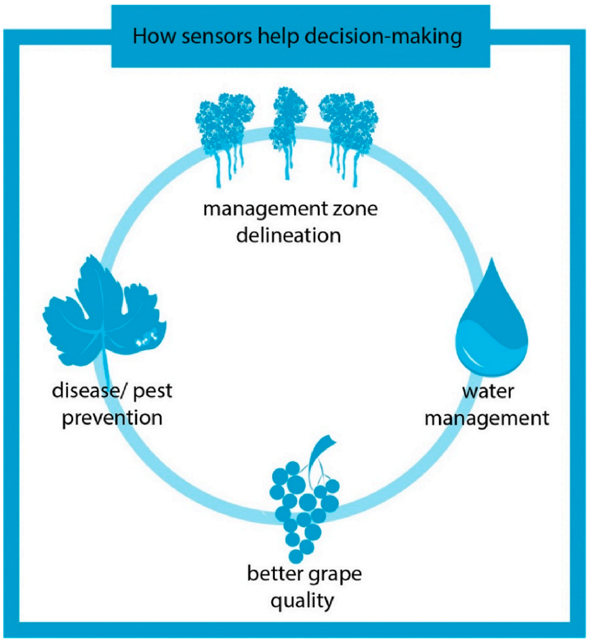

Fig. 5. Graphical representation of the identified themes.

collection is also important, the optimal time is between 11 and 14 h (local time). Precision irrigation is based on the spatial differences in the vineyard. Although winegrowers emphasize soil management or better timing of harvest, water management is becoming a more important issue due to the global warming ([77]). However, vine irrigation can be expensive ([19]), but this can be easily compensated for by the price premium of high-quality berries over standard berries ([78]). Moreover, higher and more stable yields should also be kept in mind.

The quality of the grape is closely related to its price. Weather and soil conditions seem to be the two main factors that influence quality. This can be supported with site-specific measures, for example, irrigation, pest/disease prevention, or optimized harvesting time.

In the case of a systematic review, the main limitations of the results are embedded in the keywords applied and searched databases. Different keywords result in different number of articles for screening. This research focused on the connection between proximal sensors and decision-making; however, sensor technology or methodological issues can also be analyzed.

In relation to this review, many future research paths can be identified. Due to its increasing popularity and usefulness, image-based technologies, most notably unmanned aerial vehicle-based aerial imagery, supported by artificial intelligence or different modelling tools, can also be analyzed. The digital impact of different sensing technologies is also of high importance. Related to data collection, processing, and management, the digitization footprint can be an efficient decision support tool [79]. Furthermore, all excluded connections can be analyzed, for example, the comparison of different technologies on a cost or profit basis or the identification of the state-of-the-art analytical tools. In addition, climate change is one of the key challenges in the vine sector as well; therefore, adaptation has utmost importance [80]. Negative impacts of climate change, such as weather anomalies or increased heat stress, can strongly influence grape yields and quality [81]. These issues further enhance the role of different sensors, as a basis of any decision support systems. This area is also less analyzed in the scientific literature.

Author contribution statement

All authors listed have significantly contributed to the development and the writing of this article.

Data availability statement

No data was used for the research described in the article.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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