Leveraging Artificial Intelligence to Manage a Sustainable Transition In Viticulture "STIV"

MODULE 2: Digital transition in viticulture

Precision viticulture represents a revolution in vineyard management, combining advanced technology, data analytics and agronomic knowledge to adapt to the climate, environmental and quality challenges of the wine sector. In this module we will explore its fundamentals, key tools and practical applications for more efficient and sustainable production.

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Content

1. Introduction to precision viticulture

Precision viticulture has become one of the strategies with the greatest impact to address the current challenges facing the wine sector, including: alterations associated with climate change; pressure on natural resources; the need to improve the quality of vine products, and traceability requirements for consumers. Precision viticulture is based on systematic observation, continuous measurement and intervention on a local scale in the field, which allows the personalized management of production according to its own physical, biological and climatic peculiarities of each subzone.

The main idea behind precision viticulture is to be able to identify and manage the **Spatial and intra-parcel variability of the vineyard**. Since the 1980s, pioneering studies by Smart (1985) and Bramley (2003) have shown that, within the same vineyard plot, there are marked and palpable differences in terms of vigor, soil moisture content and texture, sun exposure and slope, which mean inequalities in terms of grape yield and quality. Ignoring this heterogeneity leads to inefficient and environmentally unsustainable agronomic management.

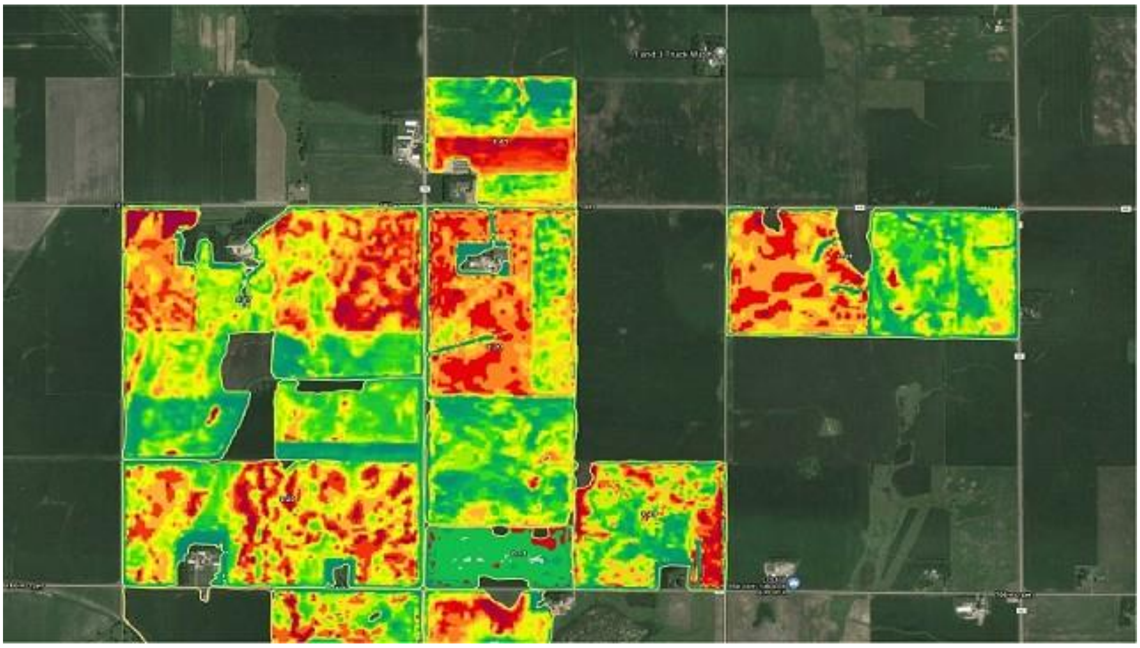


Figure 1. Heterogeneity between plots. *Source: Marcos Machado, 2022*

Precision management of viticulture is based on a set of technologies that act in an interconnected way:

- **Field sensors**, which measure soil moisture, air temperature, vapor pressure or solar radiation, can be installed at various depths and locations within the plant canopy to obtain accurate and representative data.

Figure 2. Field sensor. *Source: AGROTECH*

- **Remote sensing using satellites and drones**, measures indices such as NDVI (Normalized Difference Vegetation Index), SAVI or NDRE, all three are indices used to estimate the vegetative vigor, nutritional status or photosynthetic potential of the plant.

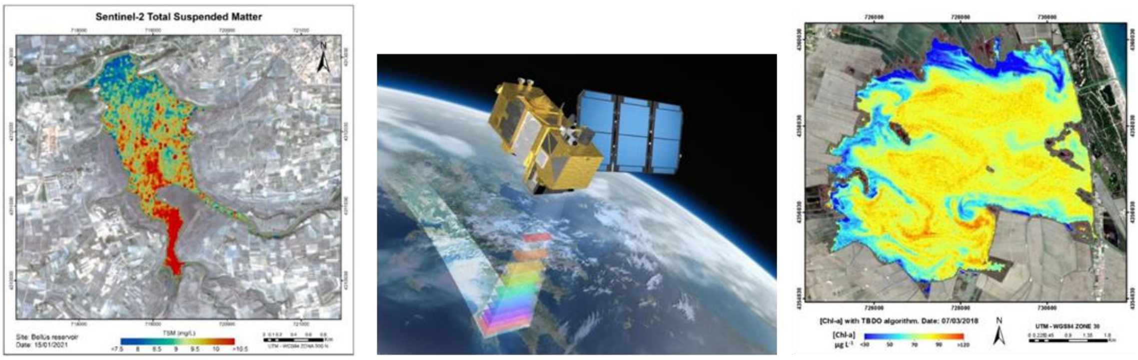


Figure 3. Remote sensing via satellite for the study of water quality. *Source: gvSIG*

- **Geographic Information Systems (GIS),** which integrate spatial and temporal data to generate zoning and agronomic prescription maps with resolutions that can range from 30 meters (Sentinel-2) to 2-5 cm (UAV). **Zoning** classifies the different soils of the vineyard to apply management adapted to each type of soil. **The prescription** is to adapt the management of fertilization and protection to the characteristics of the vineyard in the field.

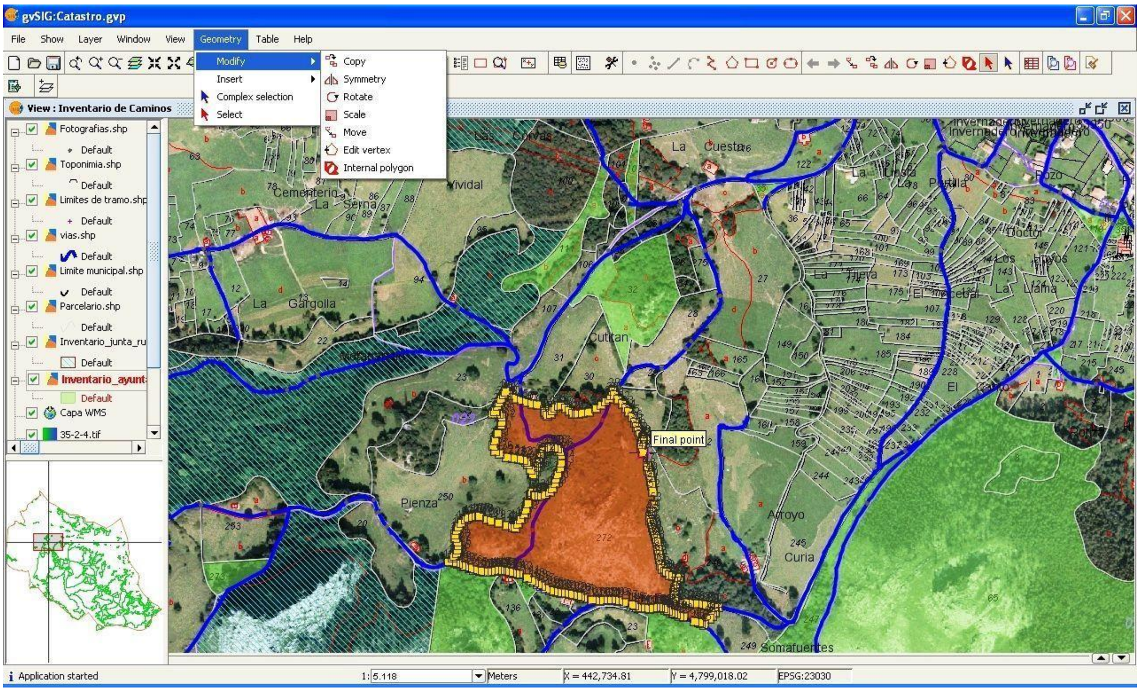


Figure 4. Zoning of a plot using GIS. *Source: Environmental Method*

- **Predictive models and artificial intelligence algorithms**, such as neural networks, vector support machines (SVMs), and random forest regression, turn data into actionable insights and recommendations. Its applications range from predicting grape yield and quality to disease detection and irrigation needs.

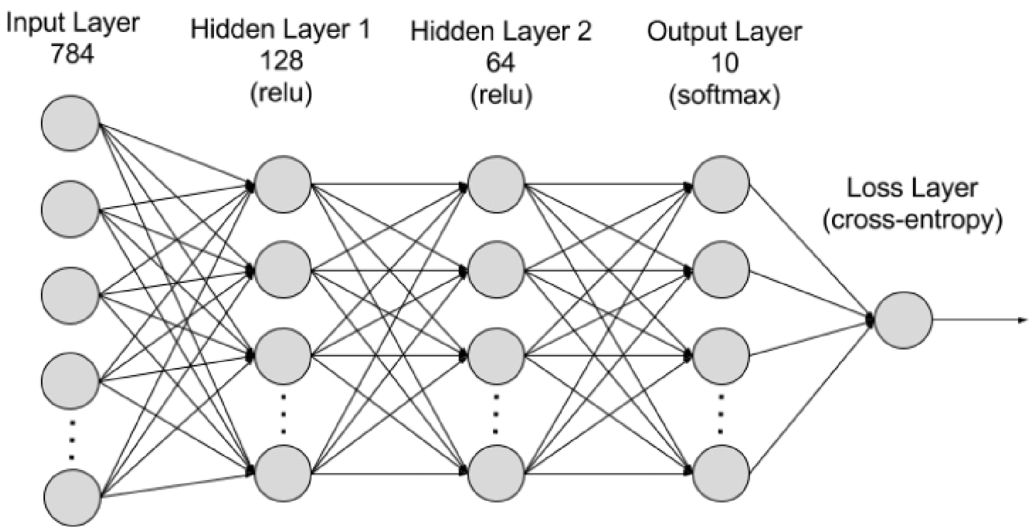


Figure 5. Operation of an artificial neural network. *Source: AWS*

- **Digital decision-support platforms** offer interactive panels, alerts, georeferenced records and real-time connectivity with machinery and IoT devices, which allows the vineyard to be managed remotely.

Thanks to these tools, the winegrower can identify Specific Management Zones (SMAs) within the vineyard and apply differentiated treatments, such as irrigation, fertilisation, phytosanitary control or selective harvesting, optimising the use of resources and improving oenological quality. For example, in regions such as Napa Valley (USA) or Maipo Valley (Chile), soil moisture sensors and NDVI maps have been used to establish sectorized irrigation lines, resulting in savings of up to 40% in water consumption without reducing productivity.

Since its initial development with differential GPS in the 90s, precision viticulture has evolved towards more sophisticated, accessible and adaptable systems. The advancement of digital technology has made it possible to democratize its use: today there are low-cost sensors, accessible drones, open-source software and cloud platforms that allow their adoption even in medium and small farms. Projects such as VineScout (Spain), GrapeLook (South Africa) or Vintel (France) have demonstrated the effectiveness of these tools in various soil and climatic conditions (Baluja et al., 2012; Matese & Di Gennaro, 2015).

In addition, precision viticulture also promotes environmental sustainability by reducing the use of phytosanitary products, minimising the water footprint and favouring biodiversity. Its integration with regenerative agriculture practices, organic viticulture and certifications such as HVE (Haute Valeur Environnementale), reinforces its role as a key tool in the ecological transition of the sector.

For all these reasons, precision viticulture is presented as a fundamental tool to promote smarter, more resilient and sustainable viticulture. It does not replace the knowledge of the winegrower, but enriches it by providing an objective and up-to-date basis for decision-making. Within the framework of the digital transition of the European agricultural sector, this discipline is established as one of the keys to achieving the objectives of the Green Deal, the "Farm to Fork" strategy and the digitalisation of the rural environment.

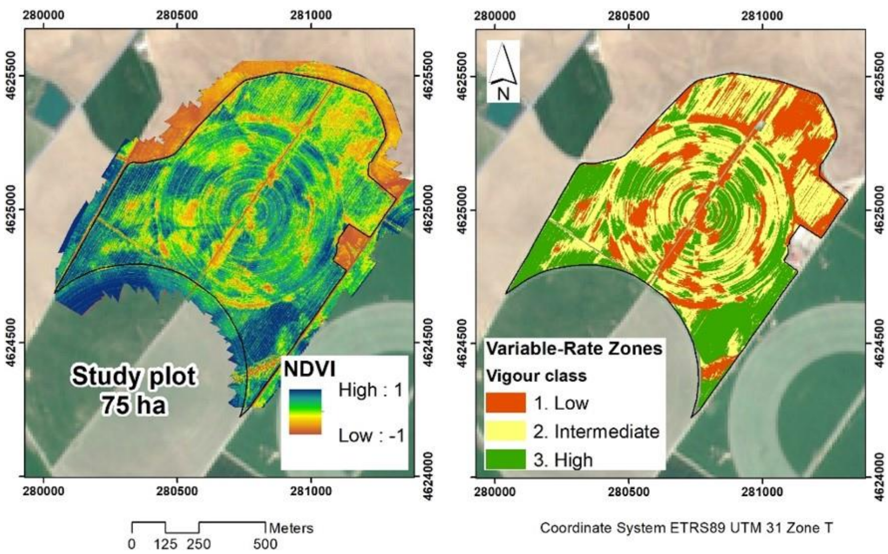
2. Fundamentals of Digital Vineyard Visualization

One of the great challenges facing precision viticulture is not only limited to data collection, but also encompasses its analysis and interpretation. As wineries incorporate sensors, weather stations, satellite imagery, and historical data, an ever-increasing amount of information is produced that needs to be processed and turned into useful knowledge. In this sense, data visualization tools and predictive models are critical to making informed decisions, especially when integrated into digital workflows ranging from data collection to specific agronomic actions.

Data visualization in viticulture

Data visualization is a way of graphically and clearly showing the quantitative information that is collected in the vineyard. Using thematic maps, interactive graphics, 3D models and dashboards, it becomes easier to understand complex phenomena such as spatial variability, the evolution of the seasons, microclimatic conditions, shoot density or leaf area index. In other words, it transforms large amounts of technical data into visual knowledge that can be understood by technicians, farmers, and winemakers, without the need for advanced training in data analysis.

Geographic Information Systems (GIS) are key tools for visualizing spatial data. Through maps of vigor (NDVI), soil moisture, yield, incidence of disease or heat stress, vintners can detect patterns and critical areas within their plots.



In practice, specific applications have been developed such as VineView, which facilitates continuous visual monitoring of the vineyard with automatic

Figure 6. Left: NDVI derived from multispectral imaging acquired in March 2019 to assess barley developmental status to determine mulch fertilization with variable dose. Right: variable fertilization zones. Source: Jensen et al. (2011)

zoning tools, or solutions such as Cropio and AgriWebb, which integrate data from sensors, machinery and weather to create digital models in real time. At the

European level, initiatives such as FutureFarm and SmartAgriHubs have made a major contribution to the development of interoperable platforms for agronomic visualization.

In addition, business intelligence tools such as Power BI, Tableau, or Qlik Sense allow you to integrate data from various sources, such as sensors, weather conditions, and soil analysis, and present it in customizable dashboards. These dashboards can be configured to send automatic alerts, generate periodic reports or simulate different agronomic management scenarios. Today, there are several commercial wine platforms, such as VineSignal, Farm360 or Datagrapes, that offer specific solutions for the wine sector, including geolocation functions, batch management, time comparison and historical visualization.

Visualization not only improves decision-making, but also facilitates communication between technicians, winemakers, field operators, and managers, allowing for more coordinated and informed management. In fact, in many modern wineries, display panels are integrated into operations control centers and are updated in real-time thanks to synchronization with weather stations, field sensors, and connected machinery.

Predictive Modeling and Advanced Analytics

Predictive modelling is based on the use of statistical algorithms and artificial intelligence techniques to predict how the vineyard will behave in the future, taking into account various observed variables. This methodology allows us to move from reactive to more proactive management, anticipating risks and optimizing the use of resources. In an ever-changing environment that is affected by climate change, having the ability to foresee different scenarios and act in advance becomes an invaluable strategic advantage.

There are several types of models used in viticulture, each with a specific focus and purpose:

1. **Phenological models**: predict when critical phases occur in the development of the vine, such as budding, flowering, veraison and ripening. These models are based on climate variables, such as cumulative temperature (degree-day), photoperiodicity, and relative humidity. Tools such as Phenoclim, VitiMeteo and STICS are able to simulate phenological development with great precision, which helps to plan more efficiently the tasks in the field and operations in the winery.
2. **Phytosanitary models**: anticipate the appearance of fungal diseases, such as mildew (Plasmopara viticola), powdery mildew (Uncinula necator) and botrytis (Botrytis cinerea). These models are based on parameters such as temperature, leaf humidity, and the amount of precipitation. Some of the most commonly used models are Goidanich's for mildew and Broome's model for botrytis. In addition, there are more complex models that include canopy microclimate variables, plant-pathogen interactions, as well as sensitivity parameters depending on the variety.
3. **Water models**: these models are responsible for calculating the water balance in the soil and the potential water stress that the plant may suffer,

using moisture sensors, meteorological data and soil characteristics. Thanks to these models, irrigation can be programmed precisely, avoiding both deficit and excess water. The combination of data from sensors and models such as AquaCrop or Hydrus has been validated in Mediterranean wine-growing regions, such as the south of France, Castilla-La Mancha or Sardinia, and has shown very positive results by reducing water consumption without affecting yield.

4. **Yield and quality models**: these are dedicated to estimating the expected production (kg/ha) and oenological parameters such as sugar content, acidity or anthocyanins. Machine learning techniques are used, such as linear regression, decision trees, artificial neural networks (ANNs) and assembly methods such as random forest, which are trained with historical and variable data in real time. In recent studies carried out in vineyards in Rioja and Priorat, random forest models have shown a prediction error of less than 10% in yield and a correlation of more than 0.85 with the expected quality of the grapes.
5. **Digital twins**: digitally represent a real vineyard, integrating all layers of information in a virtual simulation that allows future scenarios to be evaluated and interventions to be planned. These systems combine 3D modelling, system dynamics and connected sensors to represent the state of the vineyard in real time. European projects such as SmartVitiNet, VINIoT or DIGIWINE are leading this transition towards management based on twin data, with applications in planning, traceability, and simulation of agronomic strategies.
6. **Integrated socio-economic models**: in a more recent aspect, some projects are developing models that integrate agronomic factors with economic, social and market variables, making it possible to predict the economic impact of different management practices or climate scenarios. These tools are key for public policies, cooperatives and large wineries that manage complex supply chains.

Challenges and future prospects

Despite the advances, the effective implementation of these tools requires overcoming several challenges:

- Data quality, homogeneity, and standardization are critical to obtaining reliable models.
- Advanced technical and agronomic training is required to correctly interpret the results and avoid errors in decision-making.
- Interoperability between digital platforms and devices from different manufacturers remains a technical and commercial limitation.
- The initial investment can be high, especially in small farms, although the benefits are manifested in the medium and long term.

In the future, greater integration between platforms, the emergence of agricultural digital assistants (AgBots) and the massive use of generative artificial intelligence to simulate agronomic behaviors are expected. Likewise, the use of non-invasive sensors, self-adjusting algorithms and blockchain technologies will be increased to ensure the traceability and integrity of the information generated, which will contribute to strengthening transparency in the wine value chain.

3. Smart monitoring technologies in the vineyard

Intelligent monitoring in viticulture is the digital vineyard sensory system: an integrated network of devices and technologies that capture accurate and constant information about the state of the soil, the plant and the environment. This scalable and automated monitoring allows adverse events to be anticipated, resources to be optimized and informed decisions to be made. The main components of this sensory network are described in detail below, with real-world application examples and references that support its usefulness.

3.1 Wireless sensor networks on the ground

Wireless sensor networks (WSNs) applied to the soil are a fundamental innovation in precision viticulture. These networks are based on the installation of smart nodes strategically distributed in the vineyard and connected by low-power technologies such as LoRaWAN or Zigbee. The nodes are capable of measuring key parameters such as soil moisture, temperature, electrical conductivity or pH, transmitting this information in real time to a base station, the cloud and finally to digital platforms for analysis and interpretation.

The use of these networks has demonstrated tangible benefits. For example, systems implemented in wine-growing regions such as La Rioja have made it possible to reduce water consumption through irrigation that is more adjusted to weather and soil conditions. Likewise, in areas of France, similar nets have been used to detect frost conditions and activate early warnings, improving the winegrower's response capacity without the need for constant physical presence in the field.

Its main advantages include low operating costs, energy autonomy (up to several maintenance-free seasons) and adaptability to different terrain configurations. However, they require careful planning for their installation, as well as periodic calibration and verification of wireless coverage, especially in vineyards with complex orography or large extension.

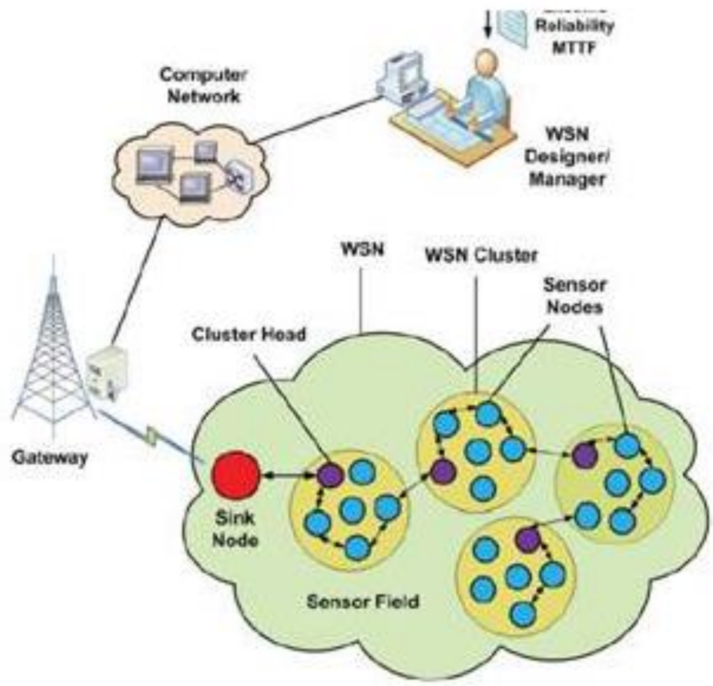


Figure 7. Wireless sensor network architecture. *Source: Bolivar et al.*

3.2 Remote sensing with drones and satellites

Aerial remote sensing has transformed vineyard management by enabling accurate, frequent, and scalable mapping. Satellites offer regular, daily or weekly coverage, useful for large-scale tracking, while drones (UAS) allow on-demand flights, capturing images of high spatial resolution (2–5 cm), which is key for parcel decisions.

Using multispectral cameras, which combine visible, near-infrared, and thermal spectra, and more advanced hyperspectral devices, it is possible to calculate a variety of vegetation indices such as NDVI, NDRE, SAVI, or GI. These indicators make it possible to evaluate the vigor of plants, detect water stress, determine the phenological state and reveal nutritional deficiencies not visible to the human eye.

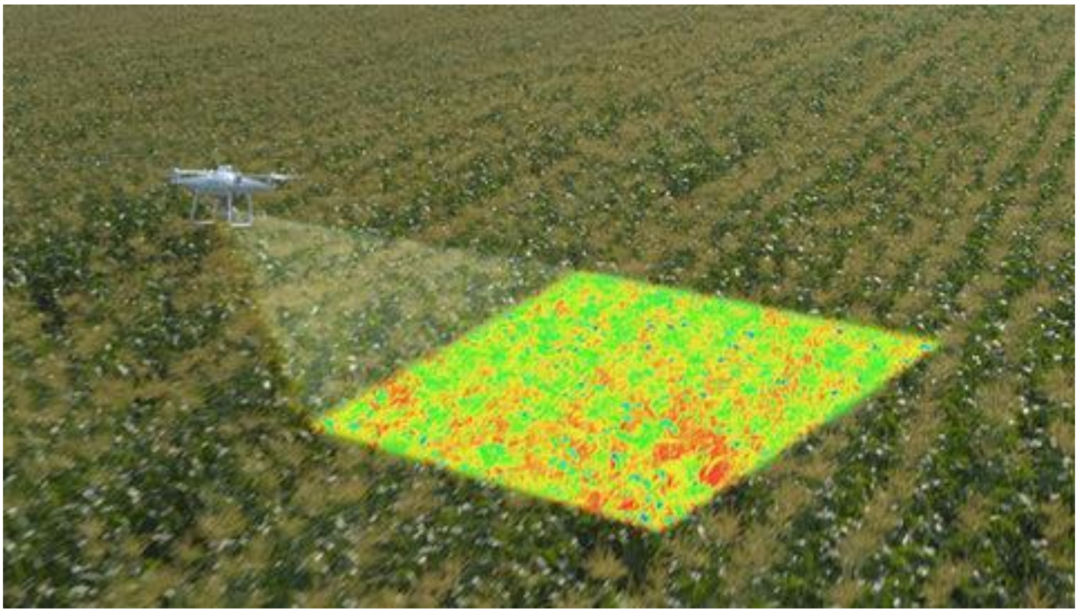


Figure 8. Remote sensing by drone. Source: Cielito Drone Enterprise

Some use cases have demonstrated their agronomic impact. In wine-growing farms, the combination of thermal and multispectral images has made it possible to anticipate diseases such as botrytis or water stress events several days in advance. It has also been documented how the weekly integration of maps into GIS platforms has facilitated more timely harvest decisions, contributing to greater homogeneity in the final quality of the wine.

More recently, the use of artificial intelligence together with this spectral data allows the early detection of pests, mildew or powdery mildew before they manifest themselves visually. Algorithms based on neural networks process specific bands of the spectrum to generate georeferenced risk maps that guide interventions.

3.3 High-resolution weather networks

Beyond direct monitoring in soil and plant, meteorological networks play a critical role in agronomic decision-making. The autonomous stations, equipped with sensors for temperature, relative humidity, solar radiation, atmospheric pressure, precipitation and wind speed, allow a dynamic understanding of the vineyard's microclimatic environment.

These systems make it possible to apply predictive models to anticipate phytosanitary risks, such as those associated with mildew or botrytis, by automatically detecting specific risk conditions. This information allows the winegrower to adapt the frequency and timing of phytosanitary treatments, avoiding unnecessary applications and achieving, in real experiences, reductions of up to 30% in the use of fungicides.

Figure 9. Weather station for cultivation. *Source: Meteosierra*

In addition, the climatic seasons make it possible to foresee extreme events such as spring frosts or episodes of heat stress. Its integration with automated platforms has been shown to reduce production losses by more than 40% through the early activationof anti-frost systems such as sprinklers or heaters.

When integrated with soil and plant sensors, these stations close the vineyard sensorization cycle, providing a holistic, multi-scale, and predictive view that improves the resilience and sustainability of viticultural management.

3.4 Foliar and sap sensors

In precision viticulture, understanding the behaviour of the soil is not enough: it is key to know how the plant responds physiologically to the conditions of the environment. To do this, specialized sensors are used to capture in real time the indicators of stress and water consumption of the vine.

Leaf sensors, designed to measure leaf turgor pressure, make it possible to detect the onset of water stress before it manifests itself in the soil. This type of monitoring makes it possible to anticipate irrigation, adjusting decisions to plant physiology and not only to edaphic or climatic parameters. These devices have been particularly useful during heat waves or prolonged droughts.

Figure 10. Folial sensor for water loss detection. *Source: Um Só Planeta*

On the other hand, sap flow sensors quantify the flow of water transported from the roots to the crown. This data reflects the real water consumption of the plant and allows irrigation management to be optimised according to its effective demand. In experiments with Chardonnay and Cabernet Sauvignon cultivars, its use has managed to reduce water consumption without compromising ripening, improving the homogeneity of acidity and phenolic concentration of the must.

Both technologies make it possible to shift irrigation management from a logic based on calendar or soil sensors to a strategy focused on the real and dynamic response of the plant, increasing water efficiency and oenological quality.

3.5 Integrative Platforms and Agricultural IoT

The true usefulness of digital technologies in viticulture arises when they are integrated into a coherent architecture that allows dispersed data to be transformed into precise and automated agronomic decisions.

Advanced platforms combine information from soil moisture sensors, weather stations, drones and satellites in a single interface. This integration allows to visualize dynamic maps of water stress (CWSI), vegetative vigor, health status and pest distribution. Based on customized algorithms, the system proposes management actions such as sectorized irrigation, phytosanitary applications or preventive alerts. In addition, it can be integrated with automated irrigation systems by means of intelligent valves, which are activated according to defined thresholds.

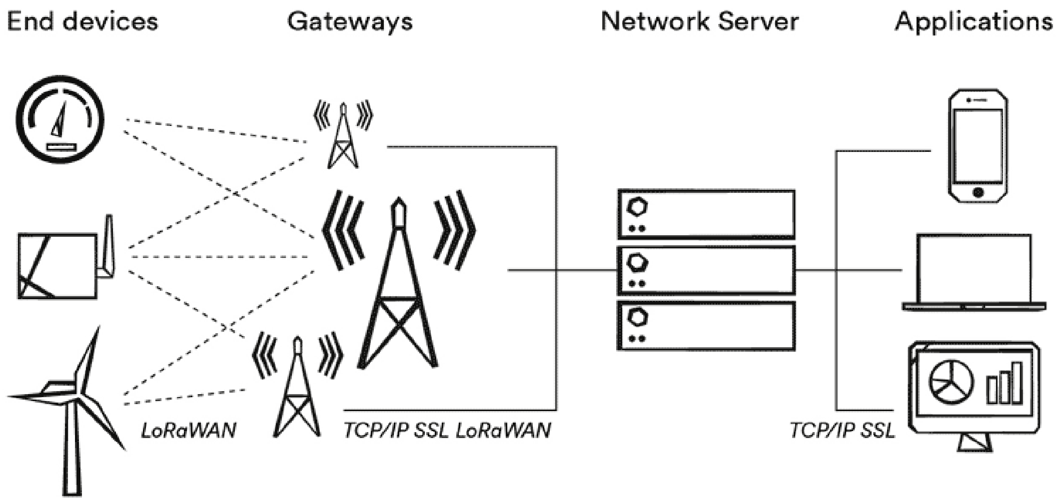


Figure 11. LoRaWan system. Source: Actility

In areas with connectivity limitations, long-range, low-power (LoRaWAN) communication networks have demonstrated their ability to keep monitoring stations running autonomously for more than a year, transmitting data at regular intervals without the need for external electrical infrastructure.

The current trend is towards collaborative and open platforms, where different actors in the sector share information for benchmarking, territorial monitoring or applied research. This synergy not only increases individual efficiency, but also generates collective intelligence for decision-making on a regional scale.

4. Predictive Modeling and Advanced Data Management

The transformation of agronomic data into actionable intelligence is at the heart of the digital vineyard. Using advanced visualization systems and predictive modeling, winegrowers can anticipate trends, assess risks, plan tasks, and improve qualitative and economic results in each campaign. This section details how these tools work, what technologies they incorporate, what results they offer and how they are applied in practice.

4.1 Geographic Information Systems (GIS) and interactive maps

Geographic Information Systems (GIS) are a fundamental tool for precision viticulture, as they allow multiple layers of spatial information to be integrated and analyzed. These layers include altimetry, vigour maps derived from vegetation indices (such as NDVI), soil mapping, local climate and historical plot yield. With this data, it is possible to generate prescription maps that delimit Specific Management Zones (SMAs), guiding differentiated decisions on irrigation, fertilization, pest control or selective harvesting.

In Europe, there are several examples of application. In Spain, platforms such as SIGPAC and the Geoportal of the National Geographic Institute allow winegrowers and technicians to access parcel information and combine it with soil and topographic layers. In France, regions such as Bordeaux and Burgundy have developed terroir mapping systems (e.g. Vitimap) that integrate climate and soil data to characterise viticultural suitability. In Portugal, the VineGIS project in the Douro Valley combines GIS with sensors and satellite remote sensing for integrated vineyard management. In Italy, initiatives such as WineGIS in Tuscany and Piedmont have made it possible to correlate grape varieties, soil and climatic conditions and management practices.

On a continental scale, the European Copernicus programme and Sentinel-2 satellite imagery have become a key source for regular vineyard monitoring, facilitating vigour mapping and detection of intra-plot heterogeneities. Likewise, commercial platforms such as Terranis (France) or EviWine (Italy/Spain) offer solutions that integrate GIS, satellite data and predictive models to optimize the management of inputs.

More recently, the incorporation of hyperspectral images captured by drones and the use of machine learning techniques have made it possible to detect critical areas within the vineyards without the need for manual intervention. These innovations significantly reduce analysis time and improve accuracy in the delineation of EMAs, contributing to a more sustainable and efficient management of resources in European viticulture.

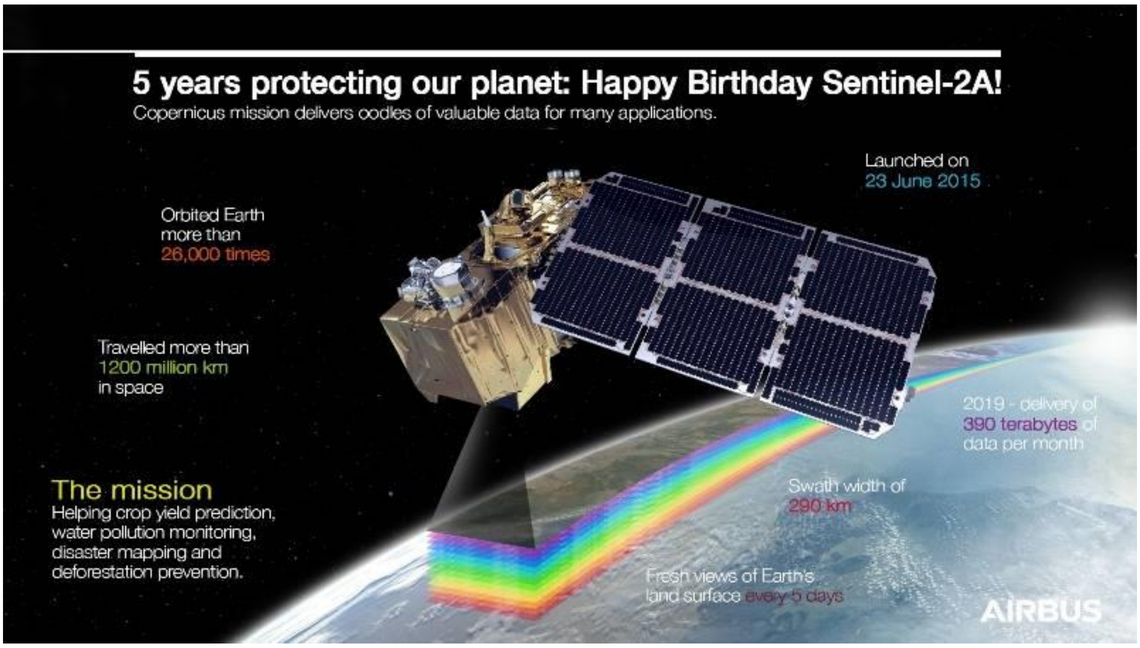


Figure 12. 5th anniversary of Sentinel - 2nd Source: AIRBUS

4.2 Dashboards and digital platforms

Today's digital platforms don't just present static maps: they turn sensory and remote data into interactive visual experiences, accessible from computers, tablets or mobiles. These tools allow winegrowers to manage their vineyard dynamically and based on real-time data.

Some of the most relevant features include:

- **Interactive time curves**, which show the evolution of key indicators such as NDVI, soil moisture, ambient temperature or water stress.
- **Georeferenced alerts**, categorized by risk levels (low, medium, high), along with precise operational recommendations such as "activate drip irrigation in sector A" or "apply urgent phytosanitary treatment".
- **Year-on-year comparison of campaigns**, allowing the identification of deviations or anomalies in the development of the crop compared to previous years.
- **Digital registration of interventions**, such as irrigation, phytosanitary applications or harvests, with detailed information on date, dose and location. These data enrich the system and strengthen its capacity for future recommendation.

Platforms such as *vite.net®* or *AgriWebb* allow you to manage the entire production cycle from your mobile phone. In Europe, a pilot validation showed that an interface designed in direct collaboration with users reduced the time required to interpret agronomic information by 40%(CORDIS, 2023).

Figure 13. Real-time management from the mobile device.   Source: AgriWebb

4.3 Predictive models and artificial intelligence algorithms

Performance Prediction

Within the framework of precision viticulture, **yield prediction** has become an essential tool not only for agronomic planning, but also for the **logistical, commercial and financial management** of wine farms. The integration of machine learning and deep learning techniques in the analysis of multi-source data (satellite images, climatic variables, field sensors and historical records) allows for highly accurate anticipation of grape production and various quality indicators at different times of the phenological cycle.

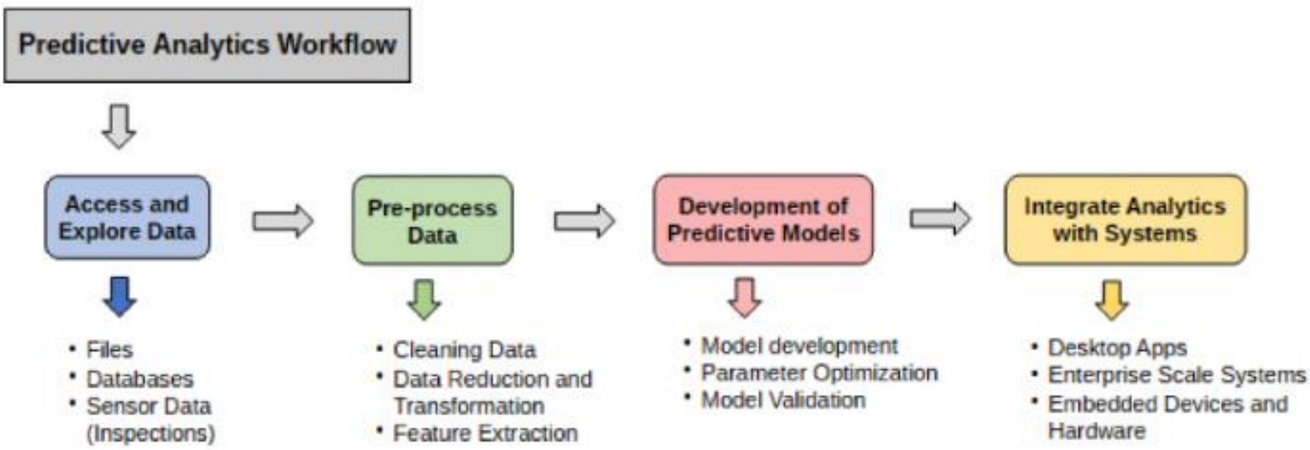


Figure 14. Predictive analytics workflow.   Source: Silva et al, 2021

Performance prediction with neural networks

One of the most promising approaches in the prediction of wine yield is the use of **LSTM (Long Short-Term Memory)** networks, a type of recurrent neural network capable of handling time series with meteorological data, vegetation indices and phenological dates. A study carried out in **the Alto Douro region (Portugal**), applying LSTM on **Sentinel-2** images (especially NDVI) and historical climate data, managed to predict yield with a **mean absolute error (MAE) of 672 kg/ha** and a **percentage deviation of 8%** from the actual data during the 2020 campaign. This model was successfully evaluated in different municipalities, demonstrating its usefulness in anticipating the harvest several weeks before the harvest (Fernandes et al., 2022).

Other even more sophisticated models, such as **CMAViT (Crop Monitoring and Assessment for Viticulture),** integrate multiple layers of data: climate, agronomic management, satellite imagery and expert knowledge. This model uses an architecture based on **Vision Transformers (ViT),** a type of state-of-the-art neural network that processes images as information sequences. In validations carried out in southern European regions, **CMAViT achieved a coefficient of determination R² of 0.84 and a MAPE (mean absolute percentage error) of 8.2%,** significantly improving predictions compared to classical models such as linear regression or decision trees (Gomes et al., 2023).

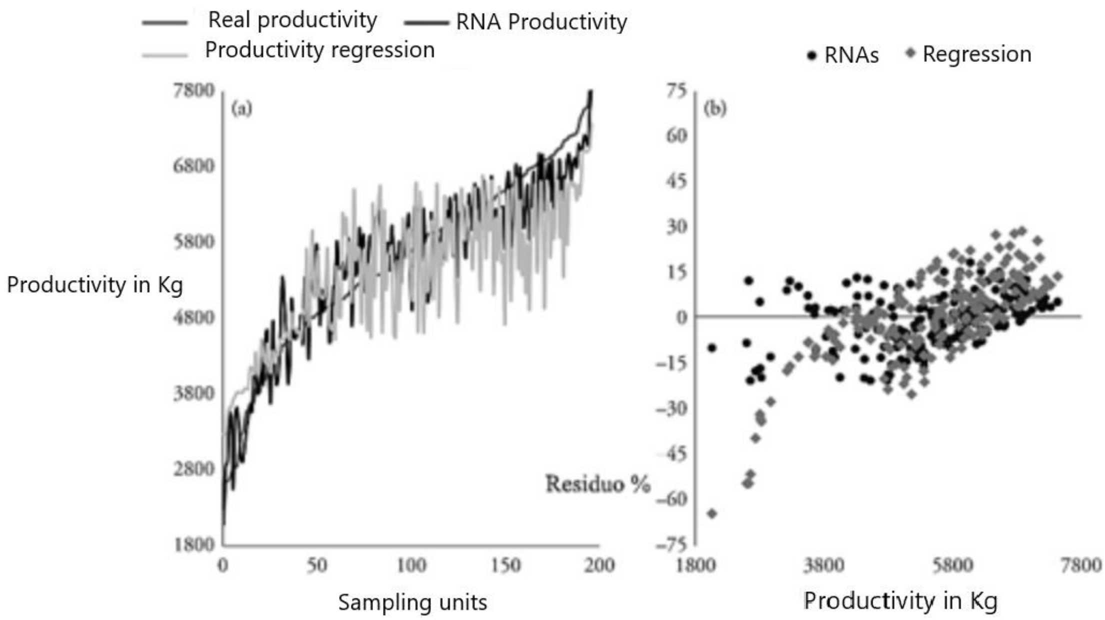


Figure 15. Predictive data modeling. *Source: Eduardo Berra Villaseñor*

Early detection of plant diseases and stress

The early identification of diseases in the vine is another of the key applications of artificial intelligence in viticulture. Through the processing of multispectral images captured by drones (UAV) and their analysis with **convolutional neural networks (CNNs),** it has been possible to detect incipient symptoms of diseases such as **mildew (Plasmopara viticola)** or **botrytis**

(Botrytis cinerea) with levels of accuracy greater than **92% at the level of thepixel**, even before the appearance of visual signs in the field (Kerkech et al., 2020).

These nets, trained with tagged images from different campaigns, have demonstrated their ability to generate **georeferenced risk maps**, which allows localized phytosanitary interventions, reducing the unnecessary use of fungicides and improving the sanitary traceability of the vineyard.

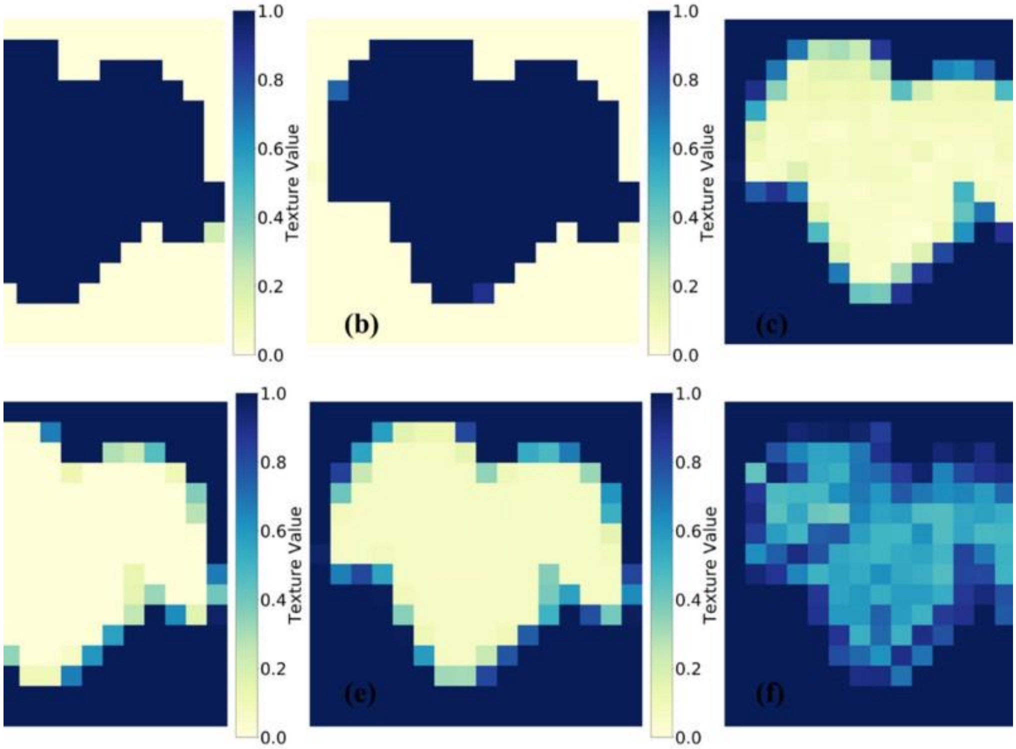


Figure 16. Diagnosis of leaf diseases using AI.Source: Elsherbiny et al.

Fruit quality estimation

In addition to the yield and health of the vineyard, artificial intelligence has also been applied to the **prediction of fruit quality parameters**, especially sugar content **(°Brix), total acidity, polyphenols** and aromatic potential. By correlating multi-temporal NDVI images captured by drones, foliar sensors, and laboratory analytical data, several studies have successfully estimated the value of these indicators.

In a recent experiment, **AutoML (Automated Machine Learning) algorithms were used** to predict °Brix based on the NDVI recorded in different phenological phases. Algorithms such as **Support Vector Machines (SVM), polynomial regression**, and **Extra Trees Regressor** offered coefficients of determination between **R^2 = 0.44 and 0.53**, results considered acceptable considering the high soil and physiological variability in the vineyard plots (Silva et al., 2021). Although still in the experimental phase, these models could allow a **differential harvest in terms of quality**, directing the optimal bunches to premium vinifications and optimising the profitability of the vineyard.

4.4 Prescription maps and VRT technology

Predictive **models applied in viticulture** not only generate analytical information, but culminate in a key operational tool: **prescription maps**. These digital maps represent the **spatial translation of the data analyses**, indicating **specific doses of inputs** – such as water, fertilisers or plant protection products – adapted to the **specific management areas (SMAs)** of the vineyard. It is one of the most advanced and tangible applications of precision viticulture, where data collection is directly converted into differentiated actions in the field.

These maps, usually generated using GIS (Geographic Information Systems) platforms, can be exported in formats compatible with modern agricultural machinery (e.g. shapefiles or GeoTIFF), and **imported directly into tractors, sprayers or fertigation equipment equipped with VRT (Variable Rate Technology)** systems. Thus, each area of the vineyard receives the exact treatment it needs, according to the diagnosis generated by sensors, models or satellite images.

Benefits and verified results

Numerous studies carried out in both Europe and America have shown the tangible benefits of using prescription maps with VRT technology in winemaking practice. For example, research conducted by the **European Union's Joint Research Centre (JRC)** in vineyards in Spain, Italy, and Germany documented **an average reduction of 20 to 30% in the use of fertilizers and phytosanitary products**, as well as a decrease in **surface runoff and diffuse groundwater contamination** (Vendrell et al., 2020). The localized application also favored a **better homogeneity in the vigor and yield of the vineyard**, contributing to a higher oenological quality.

In **Argentina**, experiments carried out in the province of Mendoza with tractors equipped with VRT dosers – fed by nitrogen maps generated by drones and data from foliar sensors – made it possible to **reduce the application of nitrogen fertilizers by 25%,** without affecting vegetative development or grape quality. In addition, an increase in nitrogen use efficiency (NUE) was observed, with lower leach losses (Castro et al., 2021).

Meanwhile, in **Chile and southern France**, the use of **smart sprayers** coupled with artificial vision cameras made it possible to detect diseased leaves with initial symptoms of powdery mildew and mildew. This detection activated application valves only in the affected areas, which resulted in **a reduction of up to 40% in the volume of fungicides used**, without compromising the sanitary control of the crop (Guillén et al., 2022). This technique also contributes to reducing waste in the final products and improves the sustainability of the winemaking process.

These experiences reflect how the combination of **modelling, digital mapping and advanced mechanisation** not only optimises inputs, but also introduces a new operational paradigm in viticulture: personalised, effective and environmentally responsible management.

Figure 17. Green Patrol automatic dispenser for pest control. Source: SmartProtect

4.5 Automated Action: Connecting Prediction with Intervention

The most advanced stage of digital viticulture is reached when the **agronomic information management cycle** is completely closed, i.e. when the data collected by sensors and processed by predictive models **lead to automated or semi-automated decisions**, executed directly on the vineyard through connected systems. This approach, known as **"from data to action",** represents the pinnacle of precision wine management, combining real-time monitoring, artificial intelligence and agricultural automation.

In this model, **decision support systems (DSS)** are no longer just consultation and analysis tools, but rather operational **platforms capable of activating physical devices**, from irrigation valves to automatic harvesters. This allows **for immediate, objective, and constant data-driven responses**, eliminating delays and reducing reliance on manual observation or subjective interpretation.

Functional examples of intelligent automation

1. **Automatic irrigation activation:** In many technified wine farms, **drip irrigation valves are connected to weather stations and soil moisture sensors**. These valves receive signals from the DSS when humidity levels drop below preset thresholds, triggering irrigation only in the necessary ZMEs and for just the right amount of time. Platforms such as **SmartVitis** and **iRooM** already integrate this functionality in vineyards in Italy and California, allowing water savings of up to **30% without reducing yield or quality** (Matese & Di Gennaro, 2021).

Figure 18. Automated irrigation. Source: verdeesvida

2. **Automatic alerts and activation of machinery:** Advanced agricultural management systems send **immediate notifications of phytosanitary risks detected by predictive models**, such as favorable conditions for mildew or botrytis. These alerts can be configured to directly trigger **autonomous sprayers or GPS-guided tractors**, if authorized by the operator, or allow real-time informed decision-making by the responsible technician. One example is the **CropX** system, which integrates canopy analysis, climate data, and forecasts to generate triggerable alerts at the plot level (CropX, 2023).

Figure 19. Crop tool for notification of alerts. Source: Cropx

3. **Segmented harvesting based on differential ripeness:** Selective **harvesting by ripeness zones** is another prominent application. DSS, using NDVI imaging and optical sensors that measure **color, chlorophyll, and soluble solids (°Brix) indices**, can identify when each ZME has reached optimal maturity. This allows the harvest to be programmed in phases, or even **to activate automated harvesters equipped with hyperspectral cameras** that select ripe bunches in real time. Some models of **smart harvesters such as the New Holland Braud 9090X** already incorporate fruit quality sensors that allow this type of advanced automation (New Holland, 2022).

Figure 20. SCF chlorophyll sensor for in-situ measurement in the field.Source: innova

Pioneering European projects

European projects such as **AI GRAPE,** which are being developed jointly by research centres in **Italy and Slovenia**, are in the implementation phase of a comprehensive platform that unifies all these capabilities: sensors in the field, analysis with artificial intelligence and **automation of tasks such as irrigation, application of phytosanitary products and harvesting**. Its objective is to create a completely closed ecosystem, where agronomic decisions are executed without human intervention, maintaining traceability and registration in the cloud (CORDIS, 2023).

This transition to intelligent automation represents the next step in the evolution of digital vineyards. It allows not only to reduce costs and minimize human error, but also to **respond more quickly and accurately to changing conditions**, such as droughts, unexpected rains or disease outbreaks. The integration of these technologies reinforces the sustainability of the production system and better adapts it to the climate and market challenges of the 21st century.

4.6 Comprehensive Case Studies

The implementation of digital farming technologies in European vineyards is generating tangible results that demonstrate the practical value of integrating sensors, predictive algorithms and automation. Below are two outstanding cases of **precision viticulture** in the Iberian Peninsula: one at plot scale in **Ribera del Duero (Spain)** and another at the regional level in the **Douro wine region (Portugal).**

Case 1: Technified vineyard in Ribera del Duero (Spain)

In a high-end vineyard in Ribera del Duero, a comprehensive intelligent monitoring and management system was implemented over three consecutive campaigns. The design included:

1. **Soil sensors and local weather stations**, installed to record continuous data on humidity, temperature, conductivity and precipitation, with reading every 15 minutes.
2. **Weekly images obtained by drones (UAVs)** equipped with multispectral cameras, allowing the calculation of vegetation indices such as NDVI and SAVI in high resolution (2.5 cm/pixel).
3. **Application of LSTM (Long Short-Term Memory) neural network algorithms**, trained with historical data on climate, phenology and previous harvests, with the ability to predict yield and the appearance of diseases.
4. **Generation of prescription maps** for the adjustment of irrigation and phytosanitary products according to specific management zones (EMZs).
5. **Irrigation automation** using valves connected to the decision support platform (DSS) and **VRT sprayers** capable of adapting doses in real time.
6. **Integrated management mobile dashboard**, where all the actions carried out were recorded, with traceability of date, dose, GPS location and operator.

The quantified results after two years of use showed significant improvements:

- **Reduction of water consumption by 30%,** thanks to irrigation scheduling based on water stress and phenological state.

- **Reduction in the use of fungicides by 25%,** through selective applications guided by predictive models.
- **Increase in the homogeneity of the vineyard yield**, with an average improvement of **+12% in kg/ha**, especially in soils with lower retention capacity.
- **Recognitions in regional quality competitions**, where the wines produced achieved superior scores in sensory evaluations and technical sheets.

This case exemplifies the potential of fully integrated digital viticulture, where agronomic action is adjusted in real time to physiological, climatic, and spatial data (González-Fernández et al., 2022; Matese & Di Gennaro, 2021).

Figure 21. Use of drones in the wineries of Ribera del Duero. Source:Computing

Case 2: Regional Prediction Model in the Douro Region (Portugal)

On a larger scale, the **Instituto Nacional de Investigação Agrária e Veterinária (INIAV)** in Portugal developed a wine yield prediction model for the **Alto Douro** region, using satellite imagery and deep learning. The system called **InfoSolo** combined:

- Multi-temporal **Sentinel-2** images with vegetation indices (NDVI) extracted during the flowering and veraison phases.
- Historical and real-time meteorological variables (average temperature, solar radiation, accumulation of degree-days).
- Training models with LSTM neural networks, capable of capturing non-linear temporal sequences.

The results indicated a **mean absolute error (MAE) of 672 kg/ha**, equivalent to a **relative deviation of 17 %.** When predictions were made at veraison, accuracy improved with errors **of less than ±8%,** sufficient for operational uses such as harvest logistics and regional macroeconomic planning (Fernandes et al., 2022).

These models were tested in several wine-growing municipalities and proved to be scalable, allowing **maps of anticipated performance** at the regional level. This facilitated **transport planning, the organization of warehouses and the anticipation of sales contracts**, as well as the validation of agricultural insurance.

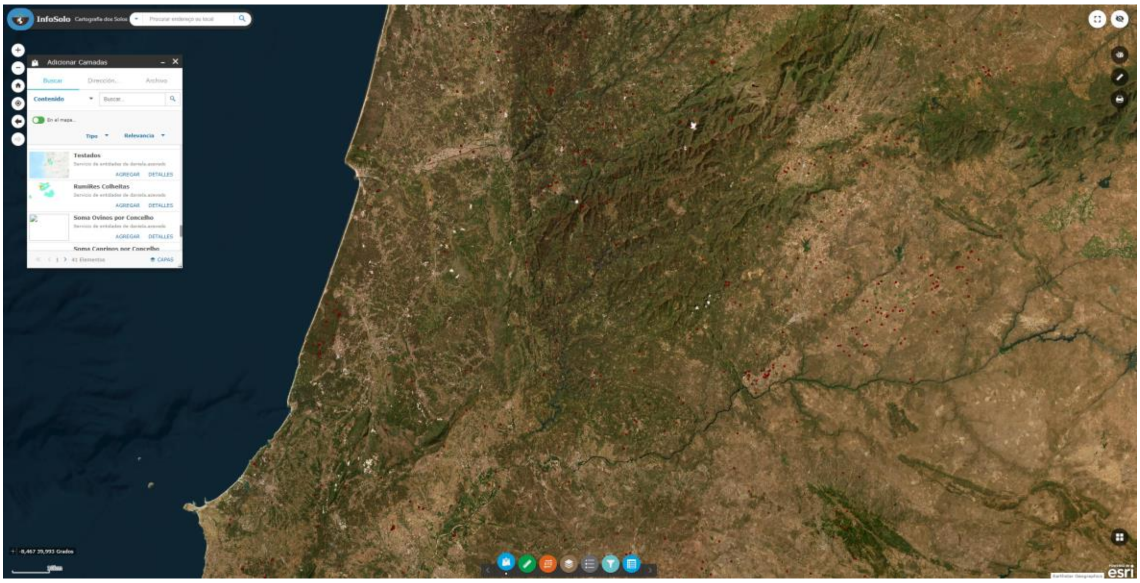


Figure 22. InfoSolo mapping system.   *Source: InfoSolo*

4.7 Benefits and challenges in practice

The adoption of digital technologies and decision support systems in the wine sector is radically transforming the processes of wine production, management and marketing. The implementation of sensors, predictive models, integrated platforms and automation allows not only to improve operational efficiency, but also to introduce a new work culture based on objective data and informed decision-making.

Immediate and verifiable benefits

1. **Decision-making based on real data:** One of the most tangible benefits of the digital vineyard is the **progressive abandonment of subjective intuition** or non-systematized experience, to move towards **decision-making based on empirical, measured and analyzed data**. This allows agronomic actions to be carried out with greater precision, coherence and traceability, which improves both management and results in each campaign (Matese & Di Gennaro, 2021; Bramley, 2009).
2. **Significant reduction in the use of resources:** Various studies show that the application of precision technologies allows the use of agricultural inputs (water, fertilizers, phytosanitary products) to be reduced in **ranges of 20% to 40%,** depending on the degree of technological integration. This efficiency not only reduces economic costs, but also **mitigates negative environmental impacts** such as diffuse pollution or the overexploitation of natural resources (Vendrell et al., 2020).
3. **Increased fruit quality and sustainability:** The possibility of localised intervention, according to the needs of each area of the vineyard, **optimises the vegetative-reproductive balance of the vine**, improves the quality of the grapes (higher concentration of sugars, anthocyanins, balanced acidity) and promotes a **more sustainable and resilient production** in the face of climate change (González-Fernández et al., 2022).
4. **Logistical and commercial anticipation capacity:** Predictive models of yield and maturity allow **the harvest to be planned in advance**, labour to be better managed and commercial agreements to be anticipated. They also facilitate in-cellar programming (reception, fermentation, pressing) and the **negotiation of purchase and sale contracts** based on verified data and not subjective estimates (Fernandes et al., 2022).

Remaining technical and organizational challenges

1. **Effective integration between hardware, software and machineryDespite technological advances, one of the main challenges remains interoperability between devices and platforms**. Sensors from different sources, analysis software, VRT machinery and management systems must be correctly integrated so that the flow of

information is continuous and reliable (Matese et al., 2022). The lack of universal standards in the agricultural sector makes this task difficult.

2. **Real-time processing and storage capacityThe volume of data generated by connected vineyards is significant, which requires data processing infrastructures in the cloud**, edge computing systems or networks with low latency. To make decisions in real time—for example, in the face of a frost alert or an irrigation recommendation—the system needs to operate with high availability and minimal delay (CropX, 2023).

3. **Development of friendly and intuitive interfacesDashboards and visualizations are often designed by developers with no agronomic experience, which makes them difficult to use by field technicians. Therefore, a co-creation between end users and designers is required**, based on principles of usability and user-centered design. In projects such as **vite.net®**, well-designed interfaces have been shown to **reduce data interpretation time by up to 40%** (CORDIS, 2021).

4. **Continuous training of personnel and calibration of the systemTechnology alone does not transform wine management. Specific training is essential to interpret the data**, understand prescription maps, calibrate sensors and adjust parameters. In addition, sensors must **be recalibrated periodically** to maintain measurement accuracy, especially under variable climatic conditions (Bongiovanni & Lowenberg-DeBoer, 2004).

5. Decision Support Systems (DSS) in Precision Viticulture

In the era of agricultural digital transformation, **Decision Support Systems (DSS)** have established themselves as the operational core of precision viticulture. Its function is to integrate, process and analyze complex information from the vineyard, generating **objective, timely and personalized agronomic recommendations**. These systems constitute the cognitive structure that allows **data to be transformed into knowledge** and knowledge into action, at the service of a more efficient, sustainable and resilient wine production (Gómez-Candón et al., 2020; Matese & Di Gennaro, 2021).

5.1 What is a DSS and what is its purpose?

A DSS can be defined as a **technological platform that combines predictive models, agronomic algorithms and real-time data** to generate practical and automated instructions in the field. As an example: a DSS designed for a winery can, at the beginning of the day, collect variables such as soil moisture, air temperature, weather forecast, satellite or drone images and the operational agenda of the field team. Based on this information, the system applies phenological models, water stress thresholds, disease predictions and predefined agronomic strategies to issue tactical recommendations such as:

- "Apply 8 mm of irrigation in the Specific Management Zone (ZME) 3."
- "Risk of medium mildew in plots with northern exposure."
- "Check phenological maturity in rows 12–16 first thing tomorrow."

This ability to synthesize and execute in real time makes the DSS a **digital agronomic assistant**, capable of operating with levels of precision and speed unattainable for manual work or traditional intuition (Bongiovanni & Lowenberg-DeBoer, 2004; Finger et al., 2019).

However, the scope of a DSS goes beyond tactical execution. These systems also act as **repositories of historical information**: they record each intervention carried out (date, dose, machinery used, operator in charge), which allows **comparative analyses to be carried out between campaigns, varietals or plots**. Thanks to the accumulation of data and the principles of machine learning, DSS can improve over time: they adjust action thresholds, recalibrate models, and further personalize their recommendations based on the history of the vineyard and the responses observed in each production cycle (Pérez-Delgado et al., 2023).

The ultimate goal of these systems is to facilitate the transition from **reactive viticulture** – which responds to problems once detected – to proactive **and predictive viticulture**, which **anticipates risks, plans ahead and optimises resources**. In this sense, DSS constitute a bridge between precision agriculture and the emerging concepts of **smart agriculture and viticulture 5.0**, where sustainability, efficiency and digitalization converge (Zarco-Tejada et al., 2014; Finger et al., 2019).

Various examples of SDM implementation in viticulture include platforms such as **Vite.net®**, developed by Horta srl in Italy, or **SmartVitis**, a project coordinated by the University of Florence, which has been validated in vineyards in Tuscany, La Rioja and Burgundy. Both solutions integrate climate sensors, multispectral images, phenological models and prescription maps, allowing action with unprecedented precision at all stages of the wine cycle.

Figure 23. DSS Vite.net risk indicators. *Source: Vite.net*

5.2 Technical architecture of a wine-growing DSS

A **Decision Support System (DSS)** in digital viticulture organizes the transformation of data into operational actions in a structured way. This flow can be divided into six main stages, each with a fundamental purpose in agronomic management:

1. Multisensory Capture

The first step is to collect information from various physical sources:

- **Soil sensors**: capacitive, tensiometric or FDR, useful for measuring humidity and electrical conductivity (Ojha et al., 2015).
- **Additional in-situ sensors**: e.g. foliar pressure meters (LeafSen), sap flow or pH sensors, which report on the physiological state of the vine (LeafSensor, 2023; Steppe et al., 2008).
- **Climatic stations**: to monitor temperature, humidity, wind, radiation, and precipitation (Jones et al., 2010).
- **Remote imagery**: satellite-operated (Sentinel-2), multispectral UAVs and thermal imaging, which allow indices such as NDVI or CWSI to be calculated (Delegido et al., 2011; Matese & Di Gennaro, 2015).
- **Manual data**: such as pruning dates, varieties, types of treatment, density of vines, among others.

The combination of these sources generates rich and heterogeneous datasets that feed the management system.

2. Data pre-processing

Before analysis, the data require processing:

- **Detection and correction of anomalous values**.
- **Periodic calibration of sensors** to adjust for bias or drift (Ammoniaci et al., 2021).
- **Temporal and spatial interpolation** to standardize data resolution.
- **Conversion of units** to operating standards (mm, °C, etc.).

This step ensures that the data is consistent, comparable, and suitable for processing.

3. Calculation Engine

Algorithmic routines process pre-processed data using:

- **Clear agronomic rules** such as degree-days (GDD) and phenological models based on BBCH phases (Brisson et al., 2003).
- **Phytosanitary alert systems** such as the GublerThomas index or EPI models for botrytis and mildew (Gubler et al., 1999).
- **Predictive models via AI:** machine learning (ML) or deep learning (DL) to estimate water stress, pest incidence or yield (Fernandes et al., 2022; Kerkech et al., 2020).
- **Generation of prescription maps** for irrigation and variable rate treatments (VRT) according to specific areas (Ammoniaci et al., 2021).

This generates hierarchical information between diagnosis and operational recommendation.

4. Action Engine

The results are transformed into concrete actions:

- **Export of VRT maps** to tractors, fertigators or sprayers, common in modern agricultural equipment (Ammoniaci et al., 2021).
- **Automated notifications**, sent via mobile, email or web, indicating when and where to act in the field.
- **Automatic activators** that manage irrigation or sprinkler valves directly through digital signals.

With this structure, the DSS ceases to be consultative and becomes an **automatic partial executor**.

5. User Interface (UX/HMI)

Interaction with the system must be clear and effective:

- **Intuitive visualizations**, including interactive maps and time curves of NDVI, humidity, water stress, etc. (Ammoniaci et al., 2021).
- **Categorized notifications** ("urgent," "review," "normal"), which help prioritize actions.
- **Geolocated record of activities**: irrigation, treatments or harvesting, with full traceability and access to campaign histories.

A good UX guarantees usefulness and adoption by technicians and winegrowers.

6. Dynamic effect and continuous learning

DSS systems operate in a **constant feedback loop**:

- They verify the results of each action (e.g., response to treatment or post-irrigation water status).
- They refine their thresholds and fit models based on observed efficiency.
- They incorporate new data into the history, allowing the algorithms to be progressively adjusted and improved (PérezDelgado et al., 2023).

This cycle makes the DSS a tool that not only executes, but **learns and evolves**.

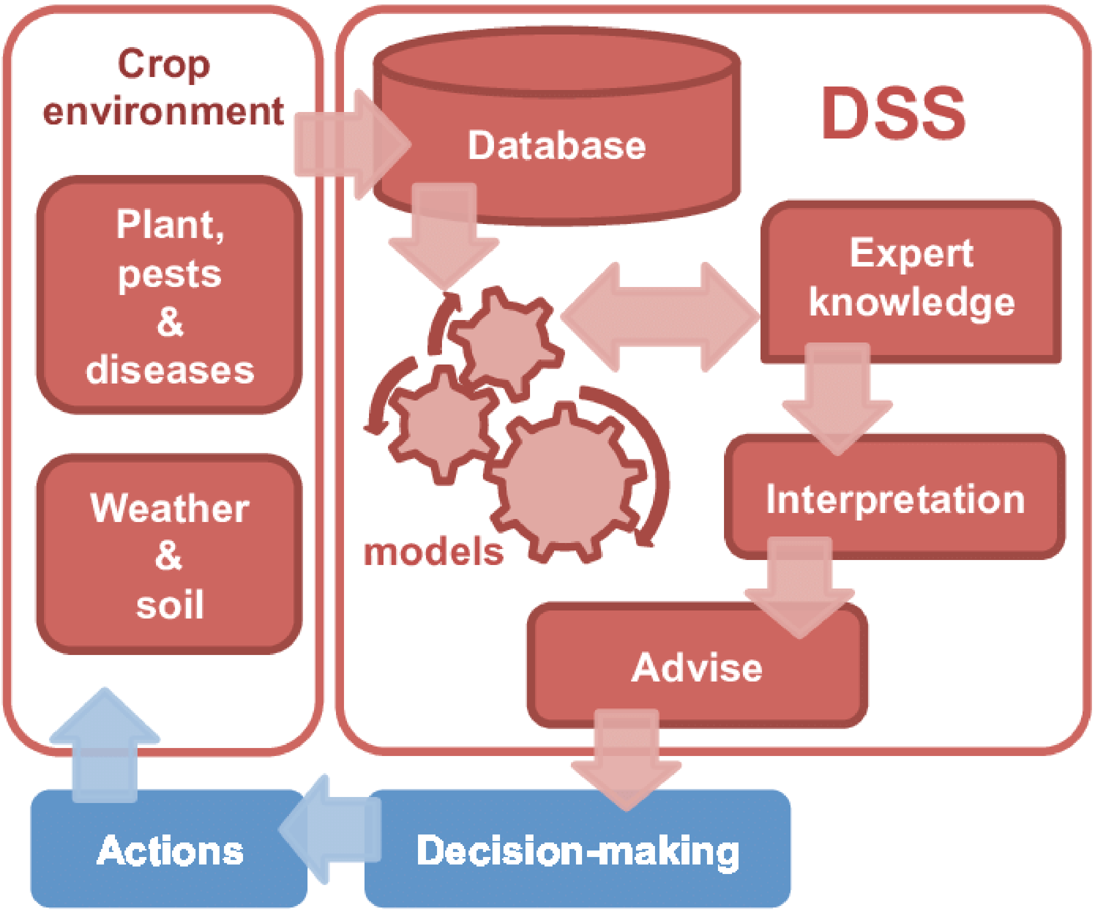


Figure 24. Example of DSS for the treatment of diseases in culture. Source: Vittorio et al. 2012

5.3 Models and algorithms used in DSS

Phenological modelling and maturity analysis

Phenological modelling combines multiple sources of information – cumulative temperature (GDD), traditional sprout and ripening dates, satellite data – to define a flexible **harvest window** of 57 days instead of a fixed date. This approach improves the adaptation of the harvest to the climatic conditions of the year, facilitating better harvest decisions (Chuine et al., 2013; Basile et al., 2023).

Phytosanitary risk modelling

Traditional ground rules, such as **GublerThomas** and the **Epidemiological Risk Index (EPI),** have been enriched by integration with artificial intelligence. These new systems incorporate variables such as temperature, humidity, evapotranspiration and microclimate by ZME, generating **automatic alerts** that avoid unnecessary fungicide applications. In some cases, its use has been reduced by up to **32%,** without compromising health protection (Gubler et al., 1999; Ayaz et al., 2019).

Water Stress Modeling

Modelling the vineyard's water balance, in combination with soil moisture and leaf pressure sensors, makes it possible to anticipate deficits and trigger irrigation before the plant is stressed. This approach has reduced water consumption by **15 to 20%,** allowing for an early and focused response (LeafSensor, 2023; Steppe et al., 2008).

Performance Prediction

Sensorization variables, weather, historical series and drone data are integrated into models such as **Random Forest** or **LSTM.** In Rioja Alavesa, an LSTM model achieved an **accuracy of 87%** when estimating kilograms of grapes per hectare using data from several campaigns (Fernandes et al., 2022).

Automatic detection of pests and diseases

The use of **convolutional neural networks (CNNs)** applied to multispectral images allows the identification of leaf spots, mildew, powdery mildew or botrytis with more than **90% reliability**, activating automatic intervention thresholds (Kerkech et al., 2020; Ayaz et al., 2019).

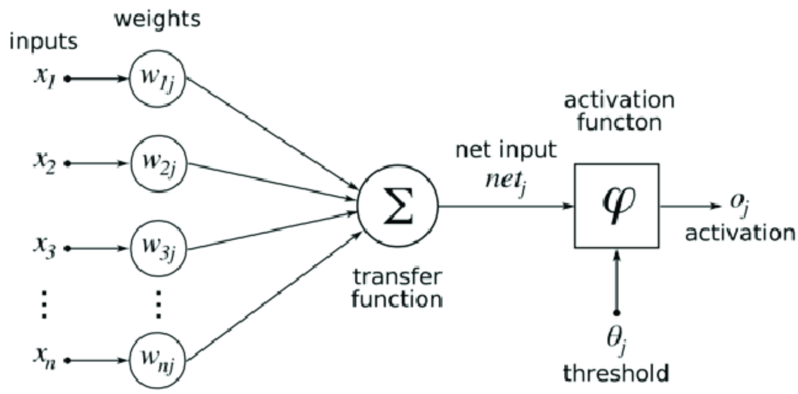


Figure 25. Schematic representation of an artificial neuron.Source: Ünal, Z. 2020.

5.4 Real experiences and field results

The development and implementation of decision support systems (DSS) has revolutionized wine management by allowing the integration of data capture, predictive analysis and visualization technologies, turning them into concrete agronomic actions. Below are some of the most representative projects and platforms that illustrate their applied potential:

VINTAGE Project

This European project implemented in key wine-growing regions such as **La Rioja (Spain), Tuscany (Italy) and Burgundy (France)** has demonstrated outstanding results in terms of efficiency. The system integrated smart irrigation, plant health and differentiated harvesting modules, with a reduction in inputs of between **20 and 30%** through segmented harvest techniques, just-in-time treatments and the use of real-time sensors (CORDIS, 2022).

One of the key points was the design of its **user-friendly interface**, which was developed and tested in collaboration with local winegrowers. Thanks to this, the system achieved a high adoption rate, demonstrating that **usability is a determining factor** in the integration of digital solutions in small and medium-sized farms.

Figure 26. VINTAGE Project

VineSens

A modular DSS system focused on family wineries and small producers, developed by a Spanish consortium. This system combines **humidity, temperature, pressure and environmental parameter sensors**, along with a simple agronomic rules engine, all integrated into an easy-to-use web platform.

In an application case in La Rioja, **VineSens made it possible to reduce water use by 18%** without compromising the health status of the vineyard, even under adverse weather conditions (VineSens, 2020). The system demonstrates that even with limited resources, it is possible to apply the principles of precision viticulture effectively and economically.

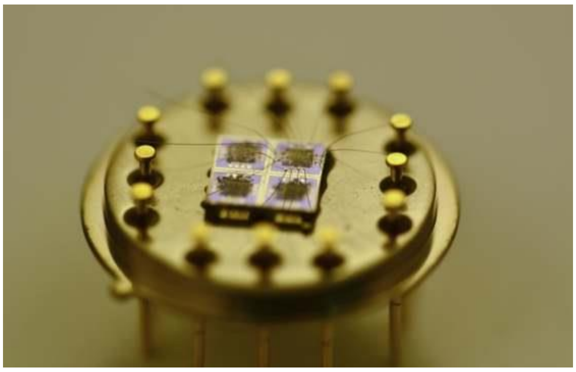


Figure 27. VinesSens sensor integration. Source: Dani Ortega

GrapeDSS

A scalable commercial platform used on multiple continents, designed for wineries of all sizes. Its modules include:

- **Balanced nutrition models**, adapted to soil and variety.
- **Rootstock selection** optimized for local climatic and pathological conditions.
- **Fumigation planning** based on phytosanitary alerts, NDVI and meteorology.

Its **mobile-first design** makes it especially useful in areas with a strong reliance on mobile devices and remote access. In addition, it allows VRT maps to be exported directly to connected machinery, facilitating differentiated agronomic management.

Figure 28. GrapeDSS Project

AI-GRAPE Project

A transnational project focused on the use of artificial intelligence for **early detection of pests** and optimized agronomic management. It is based on the combined use of **drones, field sensors and convolutional neural networks** to identify symptoms of diseases such as powdery mildew, mildew or botrytis, before they are visible to the naked eye.

Currently in the advanced stage of validation, the project aims to achieve a **20% reduction in pesticide use** and a **15% yield increase** over a 24-month period (CORDIS, 2023). Its focus on sustainability and reduction of chemical interventions positions it as a key model for ecological transition viticulture.

Figure 29. AI-GRAPE Project

WANUGRAPE 4.0

A Spanish development focused on the creation of a **modular and integrating DSS**, capable of operating in vineyards with different levels of digitalisation. The system stands out for:

- Include **water and nutrition prediction models**, even in the absence of direct sensors.
- Use algorithms adapted to **native varieties** and local conditions.
- Incorporate continuous learning logic through historical campaign analytics.

This DSS provides a reliable estimate of water and nutritional status from minimal data, making use of interpolation and field-validated rules of thumb, making it ideal for viticulture in rural areas with less technological infrastructure.

Figure 30. Presentation of the results of the WANUGRAPE 4.0 project. Source: Inagea

5.5 Essential Success Factors in a DSS

For a **Decision Support System (DSS) to** be truly transformative in the viticultural context, it must be efficiently integrated into the agronomic, social and technical reality of the farm. The key elements that determine its effectiveness are detailed below:

1. Consistent data quality

The performance of the system is directly dependent on the **reliability and consistency of the data** collected. This involves **regular calibration of sensors**, **physical verification** of field readings, and implementation of automatic procedures to detect and eliminate outliers or anomalies (Ammoniaci et al., 2021). Without accurate data, recommendations can become misaligned with reality, reducing user confidence.

2. Specific territorial modelling

Each farm has **unique microsystems**, defined by soils, vine varieties, rootstocks, and local microclimatic conditions. To maximize accuracy, models should be **customized for each context**: calibrated at the ZME (Specific

Management Zone) level, adapted to local phenological patterns, and adjusted for seasonal cyclicity (Matese & Di Gennaro, 2015).

3. Intuitive and usable interface

The actual adoption of DSS depends largely on the **user experience (UX).** The interface must offer clear dashboards, interactive visualizations, remote access from mobile devices and ergonomics developed through **co-creation with winegrowers**. Projects such as VINTAGE or vite.net® showed that improving usability can **shorten data interpretation time by up to 40%** (CORDIS, 2021).

4. Technology compatibility

A good DSS must be **technologically interoperable**: compatible with sensors from different vendors, the ability to export maps in GIS/VRT formats, and connection using standard protocols such as LoRaWAN or NB-IoT to ensure connectivity even in rural areas (Ojha et al., 2015).

5. Scaled Economic Adoption

Not all farms can take on a high level of technology investment in one go. For this reason, the systems must be **modular**, allowing them to start with basic components at a low cost (sensors, software components) and scale progressively (irrigation management, plant health, harvest). This modular strategy has been successfully applied in systems such as VineSens, GrapeDSS or WANUGRAPE4.0.

6. Continuous training

The success of the DSS depends on **human capital**. It is essential to offer **practical and constant training**, including workshops, technical support and visual resources to interpret maps, stress curves or phenological alerts. This ensures a correct application of the recommendations and encourages the appropriation of technology (Bramley, 2009).

7. Institutional boost

Finally, the support of public policies and certifications acts as **an adoption accelerator**. National or European subsidies, ecological certifications and mandatory traceability requirements have greatly incentivised investment in DSS, as they allow cost recovery, access to higher-value markets and compliance with environmental regulations (Wolfert et al., 2017).

6. Challenges and opportunities of digitalisation in viticulture

6.1 Technological and agronomic opportunities

The incorporation of digital technologies in vineyard management opens up a range of opportunities to optimise production, increase sustainability and improve profitability. These solutions allow a more precise intervention adjusted to the real needs of each area of the vineyard, thanks to the advanced collection and processing of data.

Profitability based on aerial mapping

The implementation of drones equipped with multispectral sensors has proven its effectiveness in detecting areas of greater or lesser vigour within the same plot. In studies applied in vineyards in Italy, the systematic use of these devices made it possible to detect phytosanitary problems early and differentiate management according to vegetative development. This translated into a significant improvement in profitability and a reduction in inputs by carrying out more localized interventions (Serena Sofia et al., 2025).

Optimizing Water Use

Remote sensing technologies, combined with soil and plant moisture sensors, have proven to be effective tools for improving irrigation control. These allow the water supply to be adjusted to the real needs of the vineyard, avoiding both water stress and overwatering, which has a positive impact on the quality of the grapes and the sustainability of the crop (Wang et al., 2021). Water savings without yield loss have been confirmed in several wine-growing regions of the Mediterranean, including Castilla-La Mancha, Languedoc and Sicily.

Digital traceability and added value

One of the most notable advantages of digitalization is the possibility of recording every operation carried out in the vineyard, from planting to harvesting and winemaking. This digital record not only facilitates internal management, but also allows compliance with environmental, health and quality regulations to be demonstrated. Full traceability thus becomes a marketing tool, as it offers transparency to the end consumer and makes it easier to obtain certifications such as organic, integrated production or designation of origin.

Systems that allow agricultural practices to be digitally recorded, weather conditions to be monitored, and treatments to be documented also contribute to improving the winery's sustainability image. In a context of consumers who are increasingly demanding the origin and environmental impact of products, this aspect represents a strategic differential value.

6.2 Technological and operational challenges

While the digital transition in viticulture offers endless opportunities, it also poses significant technical, economic and societal challenges that need to be addressed to ensure its large-scale adoption. This section identifies the main obstacles faced by the digitalisation of the vineyard.

High initial and maintenance cost

The adoption of advanced technologies such as humidity sensors, connected weather stations, drones equipped with multispectral cameras, agricultural data management platforms (FMIS), and variable-application machinery is a significant upfront investment. Studies carried out within the framework of the RDI Precision project in Bordeaux (Boraud et al., 2022) indicate that the total cost of a complete precision viticulture system can easily exceed €100,000, not including the costs associated with technical training, maintenance, software licenses or subscriptions to digital platforms. This economic barrier limits their access mainly to large farms or cooperatives, forcing small and medium-sized farms to opt for sharing economy models or on-demand services (SaaS).

Limited interoperability between systems

One of the biggest challenges in the agricultural digital ecosystem is interoperability between different devices and platforms. Often, field sensors use different protocols (LoRaWAN, NB-IoT, Zigbee), while tractors and machinery operate with closed interfaces or proprietary standards. This lack of integration forces specific developments or complete solutions to be purchased from a single supplier, which increases costs, generates technological dependency and limits the flexibility of the system (Wolfert et al., 2017). The need to establish open standards and interoperability frameworks is critical to moving towards effective and accessible digitalization.

Big Data Management in the Agricultural Environment

The intensive digitalization of the vineyard involves the daily collection of thousands of data from sensors, satellite images, UAVs, weather stations and management platforms. This accumulation of information, if not managed properly, can become a problem rather than a solution. The challenge is to ensure secure cloud storage, support for external APIs, filtering of useful data, and the ability to visualize it in real-time in a way that is understandable to technicians in the field. This requires not only cloud computing infrastructure, but also personnel with advanced IT and data science competencies (Kamilaris et al., 2017).

Local calibration and seasonal adjustment

For sensors and predictive models to work accurately, it is essential to perform specific calibrations for each plot, variety and microclimate. For example, a mildew prediction model trained in Bordeaux may not work properly in Priorat if it does not fit the local phenology and canopy conditions. This need for continuous calibration and validation calls for field sampling, agronomic analyses, sensitivity adjustments, and quality control of the data year after year (Tisseyre et al., 2018).

Connectivity problems in rural areas

The lack of telecommunications infrastructure in many rural regions remains a critical obstacle to the adoption of digital solutions. In some wine-growing areas of Spain, Portugal or Eastern Europe, as well as in developing countries, there are still limitations on access to mobile networks or high-speed internet. This prevents the continuous use of cloud-based services or the real-time integration of IoT devices, forcing the installation of local solutions such as LoRaWAN networks or offline storage systems (Verdouw et al., 2021).

Privacy, Governance, and Data Ownership

As vineyards become digitalized, the amount of data generated multiplies, raising important ethical and legal questions about their management and ownership. Many farmers express concerns about the unauthorized use of their data by technology providers or digital platforms. The European Union has recognized this problem and, through the European Data Strategy, has established that agricultural data generated in the field belongs to the producer, requiring compliance with the General Data Protection Regulation (GDPR) and promoting specific regulations for the agri-food sector (European Commission, 2020).

6.3 Human and cultural challenges

The transition to digital viticulture not only involves the adoption of advanced technologies, but also a profound change in the mentality, organizational culture and social dynamics of the agricultural environment. Human and cultural challenges are often more complex and persistent than merely technical ones, as they involve values, beliefs, and habits rooted in generations of work in the vineyard. The main obstacles in this critical dimension of digital transformation are discussed below.

1. Resistance to change

The reluctance to adopt new technologies is one of the factors that most limits the expansion of precision viticulture. In traditionally wine-growing regions such as La Rioja (Spain), the Loire Valley (France) or Burgundy, where empirical knowledge and direct observation of the vineyard have historically been the basis of agronomic knowledge, many winegrowers perceive digital tools as unnecessary, excessively complex or even intrusive with respect to their professional autonomy. Research carried out by DataIntelo (2023) and the University of Montpellier shows that more than 45% of winegrowers over the age of 55consider that digitalisation reduces their control over the production process and complicates decisions that were previously made "by eye" or based on direct experience.

2. Digital skills gap

The effective use of sensors, GIS platforms, dashboards, drones and predictive models requires a new set of skills that are not traditionally part of the repertoire of wine operators. Concepts such as NDVI, evapotranspiration, regression or machine learning, for example, require basic knowledge of statistics, computer science and data management. The existence of this skills gap has been documented by the European Commission, which notes that more than 60% of rural workers lack basic digital skills (European Commission, 2020). This forces farms to incorporate new technical profiles or train their workers, which represents an additional investment in time and resources. Some effective solutions have been the creation of local associations or cooperatives that group vineyards and finance joint training or the shared hiring of specialized technical personnel.

3. Transformation of the agrarian organization

Digitalisation radically changes the operational flow of a wine farm. It is no longer enough to perform tasks according to the traditional agricultural calendar; It is now necessary to coordinate field actions according to digital alerts, make decisions based on prescription maps, record each operation on mobile platforms and adapt agronomic protocols to intra-plot variability. This change involves a redesign of work routines, a new distribution of functions within the work team, as well as a more dynamic and data-sensitive planning. According to studies by the University of Padua (Zambon et al., 2019), this organizational transition requires agronomic leadership, participatory planning, and especially the involvement of technical managers in all stages of the digitalization process.

4. Need for inter-agency collaboration

Digital transformation cannot be done alone. Experience shows that its adoption is most effective when it occurs in collaborative environments, such as cooperatives, designations of origin (DO), agricultural associations or technology clusters. These networks allow for the sharing of sensors, knowledge, tools, and technical services, reducing costs and accelerating the learning curve. Collective pilot projects, such as those developed within the framework of SmartAgriHubs or the Vitinnova cluster in Spain, have shown that collaboration facilitates access to emerging technologies, fosters trust between actors and generates a more open and proactive culture of innovation (Wolfert et al., 2017).

In this sense, the existence of good local governance that articulates these collaborations, guarantees equitable access to resources and promotes technical training activities adapted to the real needs of winegrowers is also essential.

6.4 Economic considerations and adoption models

The deployment of digital technologies in viticulture has important financial and strategic implications. The main considerations that influence its effective adoption are described below:

Impact on return on investment (ROI)

Studies by agricultural economists estimate that investment in digital technologies pays for itself in just **3 to 5 years**, especially in farms of more than 20 ha or cooperatives that take advantage of economies of scale. This return comes from the reduction in water consumption (2030%) and in the use of chemicalinputs, as well as access to premium markets thanks to product differentiation and improved perception of quality (Serena Sofia et al., 2025; Farmonaut, 2024; Tey & Brindal, 2012).

SaaS and managed service models

Agricultural platforms are increasingly offered under the **SaaS (Software as a Service) model**, which bundles sensors, digital platform and technical support through an annual subscription. This approach eliminates the need for a high initial investment, adapts the cost to the number of hectares or sensor points, and facilitates the gradual adoption of the technology (Saiwa, 2023; Wikipedia, 2024).

Grants and certifications

Agricultural aid – such as that from the Rural Development Programme (RDP), European or national funds – and organic or integrated production certifications represent a significant economic incentive. Part of the cost of digitalisation can be covered through these lines of support, motivating wineries to participate in collaborative initiatives that also provide reputational benefits and access to specialised market niches.

Progressive deployment of technology

An effective strategy for implementing these solutions is to do it **in phases**:

- **Phase 1: Installation of climate station and soil sensor.**
- **Phase 2: Incorporation of drones for aerial mapping.**
- **Phase 3: Adoption of VRT machinery and automated irrigation systems.**

This approach makes it possible to evaluate specific results at each stage, adjust the budget according to impact and reduce financial risks, facilitating the progressive scalability of the investment (Kent Downs, 2021).

6.5 Emerging trends

Five key trends in the technological and agronomic development of digital vineyards are identified, with their corresponding potential for integration into wine management systems.

1. Self-focused robotization

Developments in autonomous robotics for specific tasks such as pruning are advancing rapidly. Robotic platforms such as **Bumblebee** – designed for pruning individual strains – and **HyQReal** – a quadrupedal robot – have demonstrated technical feasibility, achieving an accuracy of **87%** and a pruning duration of **213 seconds per vine**. These figures come from work presented in academic repositories such as arXiv and ResearchGate. The global robotization market in viticulture generated **USD 234 million in 2024**, with forecasts to reach **USD 690 million by 2033**, representing a compound annual growth rate (CAGR) of 13% according toDataIntelo (DataIntelo, 2024).

2. Explainable and integrated AI

The concept of **Explainable Artificial Intelligence (XAI)** is gaining ground on platforms such as **AI-GRAPE,** where models not only issue pest alerts five days in advance, but also allow human validation of these alerts before applying treatments. This hybrid interface has been shown to reduce pesticide use by approximately **20%,** by avoiding false alarms and optimizing input application (CORDIS, 2023).

3. Blockchain and transparent traceability

Blockchain technology offers the infrastructure to record each intervention in the vineyard – irrigation, treatments, harvest dates, machinery used – in an unalterable and verifiable way. This level of traceability strengthens the credibility of the product and supports price receipts in premium, organic or designation of origin (DO) markets, by allowing producers and consumers to follow the complete journey from the vine to the bottle (Kamilaris, 2019).

4. Autonomous and energy-efficient hardware

The durability and autonomy of devices in the field is essential for a sustainable system. Sensors equipped with **solar panelectricity**, self-powered LoRa nodes and integrated devices significantly reduce maintenance and recharging costs. These devices, optimized to operate for several years without intervention, guarantee continuous data collection in isolated environments or with low infrastructure (Ojha et al., 2015).

5. Universal data standards and open APIs

The lack of interoperability remains a barrier in agricultural technology integration. The adoption of emerging standards such as **ISO SmartAgri or the** FSIS (Farm Sensor Interoperability Standard) **metadata format** will enable sensors, platforms, and machinery to exchange data in a seamless and scalable manner. Having open APIs will facilitate the development of a **modular agricultural architecture**, with less dependence on suppliers and greater flexibility for end users (Wolfert et al., 2017).

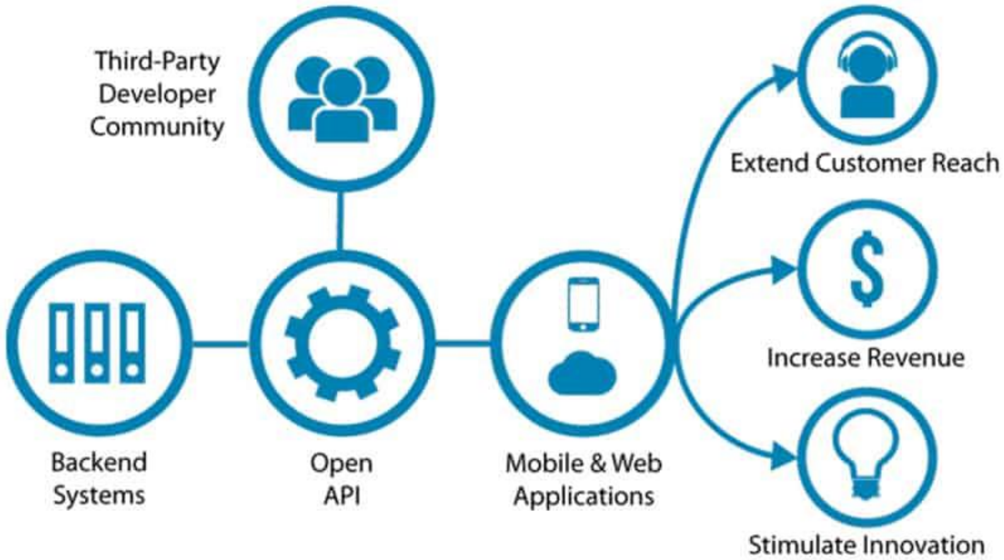


Figure 31. Structure of an API. *Source: Maplink*

7. Strategic evaluation of technology adoption

The adoption of digital technologies in viticulture is far more than an instrumental upgrade. It affects the cost structure, day-to-day work organisation, knowledge management, traceability, and increasingly the way farms interact with technology providers and regulatory requirements. For that reason, investment decisions should not be driven by tool availability or market trends alone, but by a strategic assessment that connects technology to a real need, the farm's capacity to use it, and the expected return.

Institutional evidence and comparative analyses agree that digital technologies can improve productivity, sustainability and resilience, but their impact depends on enabling conditions: connectivity, human capital, technical advisory services, access to finance, and interoperability between solutions (OECD, 2022; European Commission, Joint Research Centre [JRC], 2025). In short, technology does not "work" by itself: it creates value when it is integrated into work routines and translated into concrete agronomic and business decisions (OECD, 2022).

To keep the assessment practical, it helps to structure the decision around four guiding questions. The first concerns **value**: what specific benefit is being pursued (water efficiency, quality, harvest coordination, traceability, climate-risk reduction). The second is **total cost**: not only the purchase price, but also licences, maintenance, replacements, training and the time required to manage data. The third concerns **capabilities**: who will use the system, who will interpret outputs, who will maintain equipment, and what external support will be needed. The fourth addresses **risk**: vendor dependency, obsolescence, connectivity constraints, and data governance (OECD, 2022; McFadden et al., 2022).

Table 1. Practical evaluation framework (the "4 questions")

Dimension	Key question	What should be clear before investing
Value	What concrete improvement do we seek?	Operational indicators (e.g., reduce irrigation, homogenise ripening, strengthen traceability)
Total cost	What is the real cost over 3–5 years?	Purchase + installation + licences + maintenance + replacements + data management time
Capabilities	Who uses it and who maintains it?	Roles, training, routines, technical support, continuity during peak season
Risk	What dependencies does it introduce?	Vendor lock-in, interoperability, data rights, connectivity, cybersecurity, obsolescence

7.1. Advantages and disadvantages of digital technologies

Every innovation creates opportunities, but it also introduces new dependencies and complexity. Understanding this duality is essential to avoid investments driven by unrealistic expectations or commercial pressure. In agriculture—and especially in high-value crops such as grapes—the most consistent benefit appears when digital information enables a shift from “average” decisions (“one parcel, one rule”) to decisions grounded in real variability: different soils, microclimates, vigour patterns, or water status within the same block (OECD, 2022; JRC, 2025).

One of the most robust contributions is improved decision-making and risk management. Remote sensing (satellite or UAV) and vigour or stress maps help identify within-parcel heterogeneity, track its evolution, and guide interventions (irrigation, selective harvest, prioritisation of operations). In viticulture, technical literature confirms that each platform offers a different trade-off between spatial resolution, revisit frequency and cost; selecting the right option depends on the farm’s goals and scale (Matese et al., 2015). When climate, soil and plant data are integrated into decision-support systems, farms can better anticipate “when to act” and “where to act,” reducing operational uncertainty. OECD highlights that the value of digitalisation increases when data becomes actionable decisions, rather than multiplying indicators without a clear interpretive framework (OECD, 2022).

Another common advantage is improved resource-use efficiency (water, energy and inputs), with a crucial nuance: savings tend to appear when monitoring is linked to agronomic criteria and clear response protocols. Monitoring alone rarely produces return; decisions and routines do (OECD, 2022). Digitalisation also often strengthens traceability and compliance by enabling consistent records, easier audits and stronger evidence for certifications—delivering not only agronomic value but commercial and regulatory value as well (OECD, 2022).

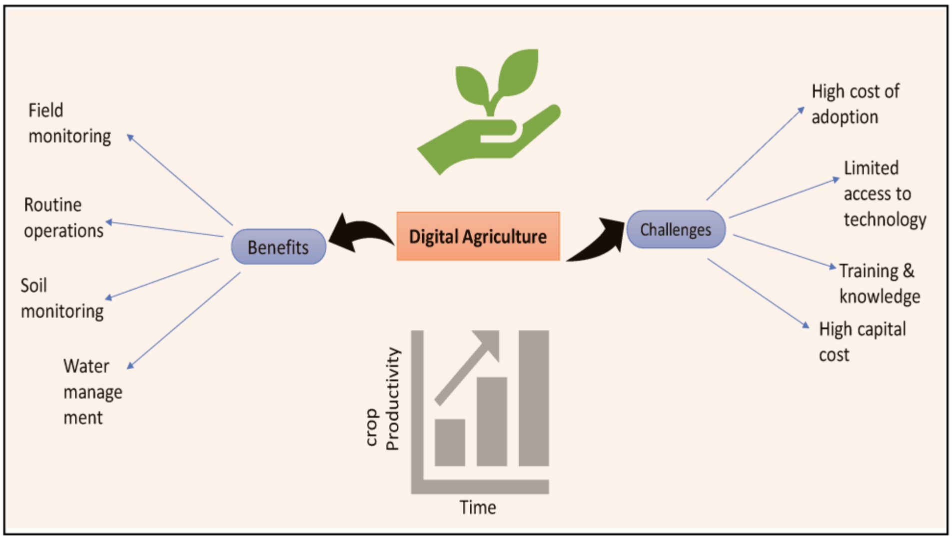


Figure 32. A schematic representation of the benefits and challenges of digitization in agriculture. Source: Seeding a Sustainable Future: Navigating the Digital Horizon of Smart Agriculture

On the limitations side, European analyses repeatedly point to structural barriers: insufficient rural connectivity, uneven digital skills, upfront and recurring costs, and technological fragmentation that makes it difficult to combine data across platforms (JRC, 2025). Data governance adds another strategic layer: who owns the data, how it is used, what happens to historical datasets, and under what conditions data is shared or monetised. OECD emphasises that trust in agricultural digitalisation is a requirement for sustained adoption, particularly for smaller farms concerned about losing control of strategic information (McFadden et al., 2022).

Table 2. Advantages and limitations by technology type.

Technology	Most frequent advantages	Typical limitations
Weather station / risk models	Operational anticipation; better planning	Requires thresholds and response routines; connectivity needed
Soil/plant sensors	Fine irrigation adjustment; stress monitoring	Installation and calibration; maintenance; interpretation capacity
Remote sensing (satellite/UAV)	Vigour maps; zoning; selective harvest	Cost/frequency/resolution trade-offs; field validation required
DSS (decision support)	Turns data into recommendations; reduces uncertainty	Depends on data quality; can feel “black box” if not understood

Technology	Most frequent advantages	Typical limitations
Digital logbook / traceability	Easier audits; orderly records; compliance	Requires disciplined recording and routine adaptation

7.2. Implementation and maintenance costs

From the producer's perspective, the decisive question is often economic: "Will this pay off for me?" Public discussion tends to emphasise benefits, but comparative evidence shows that many digital investments fail to deliver expected results because assessments underestimate recurring costs, management time, and the organisational adjustments required to make tools operational (OECD, 2022; JRC, 2025). In viticulture—where workloads are seasonal and climate uncertainty is high—this is especially critical.

The real cost of a digital system is rarely limited to the purchase price. Beyond acquisition, farms incur installation, calibration, connectivity, training, maintenance, component replacement, subscriptions/licences, and the time needed to collect, validate and interpret data. Together, these elements form the total cost of ownership (TCO), essential for evaluating profitability over a realistic 3–5 year horizon (OECD, 2022). The digital ecosystem also evolves rapidly: updates, software changes, new cybersecurity requirements, and compatibility issues can increase costs and reduce predictability (McFadden et al., 2022).

A frequently underestimated component is the organisational cost. If the farm does not redefine who checks data, who decides, when to act, and how the tool fits into day-to-day routines, technology risks being underused. In practice, part of the cost is "learning cost": the time invested to master the tool, develop protocols, calibrate thresholds, and validate outputs against field reality.

Table 3. Total cost of ownership (TCO) structure in agricultural digital solutions.

Cost block	What it includes	Where it is often underestimated
Upfront investment	Devices, installation, calibration	"I only look at the sensor/platform price"
Operations	Subscriptions, mobile data, energy, consumables	Small recurring fees that accumulate
Maintenance	Check-ups, replacement, repairs	Vendor reliance and downtime costs
Integration	Connecting systems, exports, data pipelines	Interoperability between brands/platforms

Cost block	What it includes	Where it is often underestimated
Training	Initial and ongoing skills updates	Staff learns “during season,” under pressure
Data management time	Reviewing alerts, validating data, recording	Time scarcity during peak workloads

7.3 What to assess before investing in digital technology

A robust investment decision often starts with a simple question: What specific problem am I trying to solve? International evidence consistently shows that successful implementations start from the production and organisational diagnosis rather than the tool; when technology is purchased without a clear operational purpose, abandonment becomes more likely (OECD, 2022; JRC, 2025).

In viticulture, objectives typically cluster into four families. First, efficiency goals (water, energy, inputs). Second, quality goals (zoning, selective harvest, ripening uniformity). Third, compliance and traceability goals. Fourth, risk management goals (climate, disease, operational uncertainty). Clarifying which objective dominates matters because each calls for different technologies and levels of complexity. A weather station and alerts may be decisive for disease risk management; sensor networks and mapping may be more justified in premium strategies; and a digital logbook may solve much of the compliance burden.

Once the objective is defined, a second criterion is the vineyard’s real variability. Precision agriculture tends to generate more value where within-block heterogeneity is meaningful; in highly uniform vineyards, other motivations (compliance, logistics coordination, administrative simplification) may dominate the business case (OECD, 2022). The third criterion is human: available skills and time. The EU emphasises continuing training and advisory services as key to sustaining digitalisation; without support, even well-chosen solutions can fail because they never become part of routine work (EU CAP Network, 2024).

Table 4. Proportionality matrix: “need–capacity–solution”

Farm profile	Primary need	Internal capacity	Proportional digital approach
Small/family	Alerts & planning; simplify records	Limited	Basic solutions + targeted external services

Farm profile	Primary need	Internal capacity	Proportional digital approach
Medium, quality-oriented	Zoning, selective harvest, traceability	Moderate	Sensors/remote sensing + DSS with technical support
Cooperative / many growers	Coordination, uniformity, traceability	Variable	Shared platforms + training + common protocols
Large scale/intensive	Optimisation at scale & logistics	High	Data integration + progressive automation

7.4 Progressive adoption models for digital technology

Digital transformation rarely happens in one leap. Comparative evidence shows that the most robust processes advance gradually, accumulating experience, building internal confidence, and evaluating results before scaling up (OECD, 2022). This approach is particularly relevant in viticulture, where climate uncertainty and income variability make risk minimisation rational.

In practice, many vineyards start with a "basic layer" of digitalisation: record-keeping, weather information and alerts. They then add monitoring (sensors, maps) and finally move towards integrated systems (DSS, partial automation). Layered adoption supports capability development in parallel with increasing complexity. In addition, service-based models (pay-per-use drone flights or analyses) and cooperative models (shared infrastructure and advisory capacity) can lower economic barriers and accelerate collective learning—consistent with European emphasis on training and agricultural innovation networks (EU CAP Network, 2024).

Table 5. Progressive adoption routes and when they tend to work best

Route	Description	When it is most suitable
Limited pilot	Trial in one block/season	When ROI or usability is uncertain
External services	Pay-per-use (drone, analysis, advisory)	Small/medium farms with low frequency of use
Cooperative/shared	Shared infrastructure and support	Regions with many growers and limited individual resources
Layered adoption	Basic → integrated over 2–4 years	When long-term sustainability and learning are priorities

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ANNEX I – Review Questions

Block 1: Introduction to precision viticulture

1. Explain in your own words what "intra-parcel variability" means and why ignoring it leads to inefficient and less sustainable management.

2. Compare two environmental and two productive benefits of managing Specific Management Zones (SEZs).

3. Describe a minimum workflow (in 5 steps) to move from vineyard observation to a sectorized irrigation decision.

4. Choose a factor (soil, climate, slope or sun exposure) and explain how it can affect vigour, yield and quality within the same plot in different ways.

5. Short case: a winery reports water savings of 30–40% after sectorizing irrigation. What data would be essential to justify this result and avoid biases?

Block 2: Data Visualization and Predictive Modeling for Vineyard Management

6. Distinguish between "data", "information" and "knowledge" using an example of NDVI, soil moisture and harvest decision.

7. Explain advantages and limits of using neural networks to predict performance versus simpler methods (e.g., linear regression).

8. What does "validation" and "generalization" of a model in viticulture mean? Propose a basic cross-validation protocol between campaigns.

9. Make a case where a "deceptively clear" visualization leads to a bad decision. How would you avoid it?

Block 3: Smart monitoring technologies in the vineyard

10. Compare soil sensors vs foliar/sap sensors: what they measure, when to use them, and how they complement each other.

11. Explain how a well-designed WSN (LoRaWAN/Zigbee) helps anticipate frost or water stress.

12. Differentiate the use of satellite (coverage, frequency) and drone (resolution, punctuality) for intra-parcel management.

13. What interoperability errors usually appear between GIS ↔ machinery? Propose solutions.

14. Compare expected environmental impact of VRT versus uniform management in water, N and fungicides.

Block 4: Decision Support Systems (DSS)

15. Describe the pipeline of a vineyard DSS from capture to action (6 stages).

16. Develop a use case where the DSS recommends irrigation in ZME-3: which inputs activate it and what conditions inhibit it?

17. How would you introduce continuous learning in the DSS after each campaign? Point out at least 3 parameters that you would adjust.

18. Design a mobile screen for field operators: what to see, what notifications, what quick actions.

Block 5: Challenges, people and adoption models

19. Identify three human/cultural barriers to digitalization and how to address them from training and leadership.

20. Compare equipment purchase vs SaaS/managed services: risks, recurring costs and flexibility.

21. How would you prioritize investment between weather stations, soil sensors, drone and VRT on a farm with a limited budget?

22. Present a case of collaborative economy (sharing drone/analytics in OD or cooperative): rules and benefits.

ANNEX II – Didactic Activity: " Choosing the Right Technologies for Two Wineries with Similar Problems”

The aim of this activity is to help you think strategically about digital technology adoption in viticulture.
You will analyse two wineries that face similar agronomic challenges but differ significantly in size, financial capacity, and internal resources.

Your task is to propose realistic and proportional technological solutions for each winery.

Both wineries experience the following recurring issues:

- Uneven vine vigour within the vineyard.
- Water stress during summer heat waves.
- Disease outbreaks (especially powdery mildew) after humid nights.
- Uneven ripening, leading to complicated harvest logistics.
- Pressure to reduce inputs (water, nitrogen, fungicides) without reducing yield or quality.

The difference between the two cases is not the problem — it is their capacity to invest and manage technology.

Winery A – Large and Financially Strong

- 220 hectares distributed across multiple sites.
- Full-time technical team and vineyard manager.
- Access to IT support (internal or outsourced).
- High financial capacity.
- Main challenge: coordination and consistency across many plots.

Winery B – Small and Limited Resources

- 18 hectares, mostly continuous.
- Owner-operated, with 1–2 seasonal workers.
- Limited administrative time.
- Limited financial capacity.
- Main challenge: time management and simple decision-making tools.

You may choose from the following technology “menu”:

1. Digital field notebook / traceability app
2. Weather station with mobile alerts
3. Satellite vigour maps (basic monitoring service)
4. Drone monitoring service (outsourced flights)
5. Soil moisture probes
6. Irrigation scheduling support (app or advisory)
7. Decision Support System (DSS) for irrigation or disease
8. Variable-rate application equipment
9. Team communication and planning tool
10. External agronomic advisory contract

You are not required to use technical calculations.
Focus on strategic thinking, proportionality, and feasibility.

Tasks

1. Technology Selection (Core Task)

For each winery:

- **Select three technologies for implementation during the first year.**
- **Justify your selection clearly.**

Your justification should explain:

- **Why this technology fits the winery's size and economic capacity.**
- **How it addresses the shared agronomic problems.**
- **Why it is realistic to implement within one growing season.**
- **Why you did not choose more complex or expensive alternatives.**

2. Define Four KPIs for Each Winery

For each winery, define four key performance indicators (KPIs) that could be measured at the end of the season.

KPIs should be:

- **Simple**
- **Measurable**
- **Realistic for one year**

Examples (you may adapt or create your own):

- **% reduction in irrigation water use**

- **Fewer uniform fungicide applications**
- **Improved ripening uniformity**
- **Fewer late disease interventions**
- **Reduction in administrative time**
- **Improved harvest coordination**

Explain briefly why each KPI is relevant.

3. Describe a “Data → Decision → Action” Process

For each winery, describe in words:

- **One irrigation decision process**
- **One disease management decision process**

Explain:

- **What information is collected**
- **Who reviews it**
- **How the final decision is made**
- **What action is taken in the field**

No technical diagrams are required. Clear explanation is enough.

4. Risk Identification and Mitigation

For each winery:

- **Identify two realistic risks related to technology adoption.**
- **Propose one mitigation measure per risk.**

Examples of risks:

- **Staff overload**
- **Subscription costs**
- **Lack of digital skills**
- **Over-reliance on a supplier**
- **Technology not used consistently**

5. Communication Plan

Explain how results will be communicated:

- **To management (economic and strategic perspective)**

- **To the vineyard team (operational perspective)**

Be specific and practical.