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Precision viticulture: a review

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ABSTRACT

The precision viticulture aims to optimize grape (*Vitis* spp. L.) vineyard management; reducing use of resources and environmental impacts; and maximizing quality yield. New technologies as UAVs, satellites, proximal sensors, variable rate machines (VRT) and robots are being developed and used more frequently in some parts of the world in recent years. Developments and abilities of computers, software and informatic systems to read, analyze, process and transfer a huge amount of data are major milestones in precision viticulture. In addition, different decision support systems (DSSs) for making better crop management decisions at the right time also assist vine growers. In the fragmented small vineyards in India, relatively cheaper technologies like UAV, proximal monitoring through various tools, and DSSs developed by the ICAR-NRC for Grapes, Pune, Maharashtra, India can be used by individual grape grower or through farmers' cooperatives/groups to make grape cultivation technologically-, economically- and environmentally- viable. Therefore, current status of precision viticulture technologies and their potential applications in viticulture, have been discussed.

Key words: Remote sensing, Proximal sensing, Variable-rate technology, Robots, Decision support system, Vineyard

Grape (*Vitis* spp. L.), most important fruit crop in the world, is grown in a wide range of environments (Somkuwar and Ghule, 2020). Total world grape production in 2020 was 78.03 million t from an area of 6.950 million ha (FAOSTAT, 2022). In India, grape is cultivated in almost all parts having diverse climatic conditions ranging from extreme temperate regions of Himachal Pradesh to tropical parts of South India. As per the 3rd advance estimate, India produced 2.94 million t of grapes from an area of 0.147 million ha in 2019-2020 (DA&FW, 2022). Grape is a high input crop needing application of several expensive inputs including repeated use of pesticides.

As such cost of grape production is more and indiscriminate use of inputs leads to food safety issues and environmental degradation. These problems are more pronounced in tropical dryland fruit production (Somkuwar, 2018). Precision viticulture aims at reducing the input costs by following need-based cultural/crop protection practices; applying need-based inputs; increase grape yield and quality while minimizing environmental impact (Gebbers and Adamchuk, 2010). Vineyards are generally spatially variable and heterogeneous with regard to their location, soil quality, cropping practices and weather conditions (Bramley, 2003).

They, therefore, require specific cultural and crop-protection managements to address the real needs of the crop, in relation to these variabilities (Proffit *et al.*, 2006). Recent developments in new precision farming technologies for supporting vineyard management allows improved productivity, quality, food safety and at the same time, reduce environmental impact. The essential steps in precision viticulture are assessing variation and its management. Components that are responsible for vineyard performance in terms of yield and quality vary in space and time. The spatial variability in vineyards can be assessed and mapped using surveys, high resolution satellite/aerial data and modeling.

Once variation is adequately assessed, accurate cultural (fertilizers, irrigations etc) and crop-protection (pesticides) inputs are applied in site-specific manner to reduce cost of cultivation and environmental impacts. Byju *et al.* (2020) developed fertilizer best management practices (FBMP) for three major cassava-growing regions of India using site-specific nutrient management (SSNM) and SSNM zonation maps for efficient use of fertilizers and getting better yields in cassava.

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PRECISION VITICULTURE

Precision viticulture is mainly used for optimization of inputs, differential grape harvesting, yield forecasting, and accuracy of canopy and soil sampling (Bramley and Lamb, 2003). In comparison to other crops, initiation of precision viticulture is of recent origin. This was due to the complexity of vineyard data, requirement of high-resolution images to differentiate canopy from soil and big data processing capacity to manage spatial information.

There are mainly two aspects of precision viticulture. These are monitoring technologies, that are used for mapping spatial variability and the technologies that are utilized to provide site-specific cultural inputs known as variable-rate technologies (VRTs) and robotics. In addition, supplementary technologies such as disease forecasting and Decision Support Systems (DSSs) also assist grape growers to take prophylactic actions. Available precision tools and their applications in viticulture are described below.

Information and communication technology (ICT)

Computers, mobile computing systems, internet and mobiles are major components for information gathering, processing and transferring. For collection of huge data from the fields mobile computing systems having high speed microprocessors that could operate at very high speeds were developed to store and transfer massive amounts of data. In addition to the computer hardware, there had been significant progress in development of precision farming software. Development of software for precision agriculture is more an experience than an application. The most important computer application in precision agriculture is Computer Vision (CV).

It is a technology that acquires, processes, analyses and extracts data of images to provide numerical or symbolic information such as the estimation or prediction of key traits of the targeted object, in a fast, contactless, reproducible and accurate manner (Vidal *et al*., 2013). CV comprises a set of techniques associated with artificial intelligence, that allows a computer to understand and read an image to derive precise information (Ballard and Brown, 1982). Such type of electronic integration has played important role in furtherance of precision farming during the last few decades.

Monitoring technologies

Several technologies and sensors are deployed for acquiring intra-vineyard and inter-vineyard georeferenced information. Mainly two types of technologies, viz. remote sensing technologies and proximal sensing technologies are used to monitor vineyards.

Remote monitoring

Satellites, aircrafts and UAVs (unmanned aerial vehicles or drones) are being widely used in remote monitoring.

Satellites

The Global Positioning System (GPS) is a space-based satellite navigation system that provides highly accurate, rapid and timely information. The GPS receiver calculates position of the vineyard on earth (up to 15 m accuracy) based on the information it receives from more than 4 satellites. However, a network of fixed ground-based reference stations can correct the positions indicated by the satellite systems and provide location accuracy in centimeters. The first satellite, Landsat-1 launched in 1972 was equipped with multispectral sensor and provided a spatial resolution of 80 m with a revisit time of approximately 18 days. The last launched Landsat satellite, Landsat-8 (Ridwan *et al.,* 2018) operates in the visible, near-infrared, short wave infrared and thermal infrared spectrums. Other high-resolution satellites that are being used in remote sensing are:

Sentinel-2 (https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-2-msi),

RapidEye (https://earth.esa.int/eogateway/missions/rapideye?text=rapideye)

WorldView -1, -2 and -3 (https://earthdata.nasa.gov/worldview)

Sentinel-2 data are open-source and freely downloadable. RapidEye has been used to evaluate Normalized Differential Vegetation Index (NDVI) in order to characterize the vine vigor and some phenolic parameters. Simple linear relationships between NDVI at berry set, pre-veraison and ripening has been found to evaluate sugar content and anthocyanins at harvesting (Santangelo *et al.,* 2013). RapidEye has also been used to evaluate the Leaf Area Index (LAI) in vineyards demonstrating a good correlation with in-field estimation of evapotranspiration (Vanino *et al.,* 2015). WorldView has been used to detect vineyards, canopy estimation and discrimination of varieties (Karakizi *et al.* 2016).

Aircrafts

Aircrafts monitor large areas with a long flight range and can carry heavy and multiple sensors at a time. Aircrafts provide better ground resolution (up to 10 cm) depending upon flying altitude. However, aircrafts are economically feasible only on areas bigger than 10 ha (Matese and Di Gennaro, 2015).

UAV

UAVs fly autonomously and can be controlled remotely by a ground pilot. UAVs are fixed with several flight control sensors (gyroscopes, compass, GPS, pressure sensor and accelerometers) which are controlled by a microprocessor. They can be equipped with a variety of sensors for performing a wide range of monitoring. UAVs provide very high spatial resolution on the ground (down to cm) and they are ideal for small-to-medium fields (1–20 ha), characterized by high fragmentation and high heterogeneity. There are two types of UAVs having rotary wings and fixed-wings. Rotary-wings UAVs having less flight time (up to 30 minutes) are generally used for monitoring small fragmented areas (up to 20 hectares), while *fixed*-wings UAVs having more flight time (up to 1 hour) allow monitoring large unfragmented flat areas (Ammoniaci *et al.,* 2021).

In comparison to satellites, UAVs have much higher resolution, therefore, use of UAVs with high-resolution sensors is suggested for assessing vine structure and inter-row spacing of vineyards (Khaliq *et al.* 2019). UAVs with true colour cameras (RGB) and multispectral or thermal sensors have been used in viticulture to detect vineyards/vine rows (Comba *et al.,* 2015); estimation of grape yield (Di Gennaro *et al.,* 2019); assessing vegetative vigor and detecting missing plants (Matese *et al.,* 2018); and estimating water stress and assessing grape maturity (Soubry *et al.*, 2018). UAV technology has shown to be economically compatible with the agronomic costs in vineyards with more than 40 hectares having lots of fragmented vineyards (Mondino *et al,* 2017).

Proximal monitoring

In addition to aerial monitoring, several tools having different types of sensers are available for proximal monitoring. Radiometric and fluorometric sensors and some application programmes such as VitiCanopy are used to assess canopy vigour, stress, chlorophyll content, nitrogen concentration and leaf area index. Geophysical and spectro-radiometric sensors are employed for assessing soil composition and structure. While, optical sensors (fluorometric and spectrophotometric sensors) determine grape quality and berry ripening. These sensors are mounted on farm machinery or some of them such as optical sensors are fixed on handheld devices and various measurements are carried by moving vehicles or manually for getting precise ground information. In addition, wireless sensor network (WSN) technologies configured in vineyards provide a highly useful and efficient tool for remote and real-time monitoring of important variables od vineyard.

Canopy assessment by proximal sensors

Radiometric sensors measure electromagnetic radiation reflected by vegetation and it can allow the rapid collection of important information for indirect measurement of the canopy state. The spectral response of canopy is mainly related to the radiation absorption by the pigments, which allows the assessment of vegetation cover but also the characterization of its health (Casa, 2017). If solar radiations or external light source is used, radiometric sensors are passive and results are affected by variations in lighting conditions.

But, if they use their own artificial light source, they are active and less affected by lighting variations. Also, use of inbuilt lighting by active sensors permits recording of information in night. Two commercially available radiometric sensors are OptRx (Ag Leader Technology, Ames, IA, USA) used to assess the vigor of the crop and CropSpec (Topcon, Livermore, CA, USA) used to determine chlorophyll content that can be correlated to nitrogen concentration in leaves.

Another optical sensor is fluorometer that measures fluorescence emitted by the chlorophyll. Based on this information onset of stress conditions in the vineyard can be predicted. The information derived from the fluorescence measurement represents functional state of the plant, and in turn photosynthetic potential of canopy. From this photosynthetic potential expressed as electronic transport rate (ETR) and two other parameters viz., leaf and air temperatures, Losciale *et al.* (2015) developed an index (I_{PL}) capable of estimating the rate of net photosynthesis of the leaves. Photosynthetic activity has been shown to influence fruit composition and wine quality in grape (Somkuwar *et al.*, 2014a, 2018).

VitiCanopy developed by De Bei *et al.* (2016) is one of the most used Apps to measure the LAI in vineyards. This is done through images acquired by a smartphone/tablet. The image is then analyzed by the App to calculate both the LAI and the porosity of the canopy. The results obtained through VitiCanopy are georeferenced to know the variation in the entire vineyard. Such information can be extrapolated to estimate the vigour, productivity and quality of produce from a vineyard.

Soil assessment by proximal sensors

Monitoring of soil health is one of the most important applications of precision viticulture. Wide range of sensors are used for assessing soil variability. Electrical conductivity (EC) of the soil is directly related with several soil properties such as texture, depth, water retention capacity, organic matter content and salinity. EC of the soil an be measured using mobile platforms equipped with sensors and GPS. Two types of sensors viz., Electrical Resistivity Sensors and Electromagnetic Induction Sensors are used to measure soil EC. Commercially available electrical resistivity sensors are Veris 3100 (Veris Technologies Inc, Salina, USA) and Automatic Resistivity Profiling System (Geocarta Ltd, Paris, France). While, DualEM (DualEM, Milton, Canada) and EM-31 & EM-38 (Geonics Ltd, Mississauga, Canada) are commercially available electromagnetic induction sensors. Knowledge about spatial variability of soil characteristics is important for understanding variability in the physiological response of the vines (Priori *et al.* 2019).

Other type of sensors used for soil assessment are Geophysical sensors. These sensors measure potential drop in introduced current in the soil. Such drop is related with EC. The EC of the soil is related to the soil texture, humidity, salinity, degree of compaction and the presence of gravel and pebbles in the soil. Invasive geophysical sensors (mobile soil resistance-meters) measure the apparent resistivity of the soil by using direct contact electrodes and non-invasive sensors (electromagnetic induction sensors, ground penetrating radars) assess soil properties by using electromagnetic fields. Another type of non-invasive sensor is the ground penetrating radars. These radars gather information of the soil through emission of electromagnetic pulses and phenomena of reflection and refraction of the different materials of soil.

Third type of sensor used for assessing soil is Spectroradiometer. Each soil has its own spectral signature which is the intensity of the reflected radiation depending on the intrinsic spectral behavior of soil constituents (minerals, organic matter, water etc). Gamma-ray based spectroradiometers consist of a scintillator crystal, generally, made of cesium iodide (Csl) or sodium iodide (Nal), which emits photons when hit by gamma rays. Reflected photons by the soil are measured to characterize soil properties. Vis-nir reflectance spectroradiometer is rapid and relatively cheap alternative to gamma-ray based spectroradiometer. This sensor can measure several soil properties in a single scan.

Grape quality assessment by proximal sensors

Berry quality is an important attribute from commercial angle and several cultural manipulations are made to improve bunch yield, berry quality and biochemical composition of berries (Somkuwar *et al.*, 2014b). Non-destructive monitoring of grape quality parameters is based on optical sensors. Manual devices or tools fixed with optical sensors are used for non-destructive monitoring of grape quality parameters. Some of the tools that are in common use are: Multiplex (Force-A, Orsay, France) and Spectron (Pellenc SA, Pertuis, France). Multiplex is mainly used to estimate the nitrogen status of grapevine leaves.

In addition to nitrogen status, Multiplex can also assess contents of chlorophyll, flavanols and anthocyanins in the leaves and grapes (Cerovic *et al.*, 2008). Another sensor used to assess the quality of the grapes is the Spectron (Pellenc SA, Pertuis, France). This sensor is integrated with GPS and can be used for non-destructive measurements of quality-related parameters, like sugar, acidity, anthocyanins and water content (Matese and Di Gennaro, 2015).

Yield assessment by proximal sensors

Many systems are available to obtain georeferenced yield information. These are: HarvestMaster Sensor System HM570 (Juniper Systems Inc., Logan, USA), Canlink Grape Yield Monitor 3000GRM (Farmscan, Bentley, WA, Australia), and Advanced Technology and Viticulture (ATV) (Advanced Technology Viticulture, Joslin, SA, Australia). These systems are mounted on mechanical harvesters and for yield assessment they use volumetric grape measurement on the discharge conveyor belt of the harvester and/or direct measurement of the transported grape weight by means of load cells.

Assessment of microclimate and other parameters in vineyard using Wireless Sensor Network

Wireless sensor network (WSN) technologies provide a useful and efficient tool for remote and real-time monitoring of important variables of a vineyard. A WSN consists of wireless peripheral nodes and a sensor board equipped with sensors and a wireless module for data transmission from nodes to a base station. At base station the data are stored and these data accessible to the end user for taking appropriate vineyard management decisions. Applications and configuration of WSN in vineyards has been adequately described (Burrell *et al.*,2004) and WSN has been successfully used for prolonged temperature and microclimate measurements (Matese *et al.*, 2013). The primary application of WSN is the acquisition of micrometeorological parameters at vine canopy and soil level. Recent developments of new kinds of sensors such as dendrometers and sap-flow sensors made it possible to continuously measure plant water status for irrigation scheduling.

Forecasting and decision support systems (DSSs)

Precision viticulture aims at reducing input costs; enhancing productivity and quality of the produce; and protecting environment. Reliable and timely forecasts provide useful information for planning in advance. Viticulture is highly input and cost intensive. In crops, production and attack of insect pests and diseases and production estimates are the two major aspects that need attention. Insect pests and diseases are major causes of reduction in productivity and their appearance and intensity can be forecasted based on weather parameters. Timely application of remedial measures reduces the yield loss.

Forecasts of crop production before harvest are required for different policy decisions related to storage, value addition, pricing, marketing, import-export, etc. Other tools for timely application of inputs are Decision Support Systems (DSSs). Decision support systems (Power, 2002) are interactive, computer-based systems which help users to accurately identify specific problem (mainly nutrient deficiency and incidence of insect pest/disease) based on symptoms in the vineyard. Once the problem is identified, DSS suggests management strategies for it.

In viticulture, DSSs have been of great help in making appropriate decisions at appropriate time, thereby, reducing crop losses to a greater extent. Several DSSs are available for guiding the vine growers to take suitable management strategies to address macro- and micro-fertilizer deficiencies, incidence of diseases and infestations by inset pests. Metos® (Pessl Instruments GmbH, Werksweg, Weiz, Austria) is commercially available decision support system for grape production.

ICAR-National Research Centre for Grapes, Pune, India (https://nrcgrapes.icar.gov.in) has developed some DSSs on irrigation, soil nutrition, diseases and insect pests for assisting Indian grape growers for judicious use of inputs.

Variable rate technology (VRT)

Farm machines fitted with VRT technology (sensors) and GPS make precise operations based on prescription maps prepared using remotely and proximally recorded data of the vineyard. Based on these prescriptions, these VRT machines apply various inputs (fertilizers, pesticides and other inputs) at right doses and at right places without manually changing rate settings. This is possible due to GPS module and electronics, consisting of control units and proportional servo-valves mounted on VRT machine. In order to have a standardized system of communication between tractors, software and various equipment and to allow the exchange of data and information with a universal language through a single control console integrated in the tractor cab, the ISOBUS or ISO 11783 protocol has been developed (ISO Standard. Available online: https://www.iso.org/standard/57556.html

In addition to fertilizers and pesticide applications, such thematic prescription maps can be developed for yield and quality parameters like acidity, polyphenols and anthocyanin. Another application of VRT machines is selective harvesting. Selective harvesting is split picking of fruit according to a vineyard vigor mapping, grape composition, and quality as per market demand. For example, grapes grown for juice purpose, sugar content is an important target for harvest, while, combinations of sugar content, anthocyanin content and acidity could be targets for grapes grown for wine purpose.

It has been reported that a variable rate fertilization can save up to 30% of fertilizers (Donna *et al.*, 2013) and a variable rate application of pesticides can save up to 30% of pesticides and increase the profit up to 20% (Casa, 2017).

Robots

The use of robotics in agriculture is still in infancy, however, the agricultural robotics is poised to change agricultural scenario in the world by 2050 (Blackmore, 2014). In viticulture, The VineRobot project at the University of La Rioja, Spain is aimed to develop a new agricultural robot, equipped with noninvasive monitoring technologies and GPS. Such robots are expected to perform a proximal monitoring of various critical parameters such as yield, vigor, water stress, quality of the grapes and assist vine growers to improve vineyard management. The Commercially available Wall-Ye robot (http://www.wall-ye.com/) can move along vine rows and acquire data on each vine, thereby, producing detailed vineyard map. Wall-Ye can prune about 600 plants per day and can be remotely controlled by iPad.

Another robot called VineGuard developed by Ben-Gurion University, Israel is designed for foliar applications. This robot can move within the vineyard using a complex set of sensors. Another commercially available robot is "Vitirover" (https://www.vitirover.fr/en-home). This robot was developed by Chateau Coutet (Saint Emilion, France) and it can cut the weeds up to a distance of 2–3 cm from the base of the vine. Solar power system is fixed on this robot. Several other robots and robotic tractors are under various stages of development and testing.

Precision technologies in viticulture

The introduction of new technologies for vineyard management facilitate enhancement in efficiency, productivity and quality and reduction in cost of cultivation and environmental impact. Precision technologies have been used for various purposes in vineyards.

Soil properties

Variations in soil fertility impact vineyard performance. Mobile platforms fitted with proximal soil sensors can be moved over the field to acquire geo-referenced soil data. High-resolution maps developed using this soil data and GPS provide valuable soil information on spatial variability of soil properties and topography which are relevant when establishing new vineyards and/or redeveloping existing vineyards (Bramley, 2010). Data acquired from Recently, data acquired from electromagnetic induction sensors and multispectral imaging were combined to estimate vineyard soil and vine vigour variability (Hubbard *et al.*, 2021).

Use of electrical resistivity sensors is limited to determination of soil nutrients, pH and organic matter; however, optical and electrochemical sensors can be used for assessing patterns of chemical fertility parameters of the soil (Joseph *et al.*, 2010). Performance of mobile near infrared spectrometry for in situ soil mapping and gamma-ray spectrometers for detecting the presence of particular minerals have been explored in vineyards by Schirrmann *et al.* (2013) and Simone *et al.* (2014), respectively.

Vegetative growth, nutritional status and canopy architecture

Remote and Proximal Sensing-Derived Spectral Indices and Biophysical Variables have been widely employed to evaluate vine canopy growth and health in commercial vineyards (Darra *et al.*, 2021). Nutritional status of leaf nitrogen can either be assessed using fluorescence-based portable sensors. Such sensors can also be mounted on mobile platforms (Diago *et al.*, 2016a) Another technology known as light detection and ranging (LiDAR) has been shown to be a powerful technology for the rapid and non-destructive assessment of canopy and leaf parameters in vineyards (Arno *et al.*, 2013). Some other precision viticulture applications are RGB camera imagery acquired by UAV for estimating canopy biomass and detecting missing plants (Di Gennaro and Matese, 2020) and UAV-based point cloud analysis to detect the severity in canopy decline caused by dieback-like disease symptoms (Ouyang *et al.* 2021). Canopy architecture, including fruit and leaf exposure and canopy porosity can assessed using machine vision technologies (Diago *et al.*, 2016c) or on-the-go assessment using RGB image analysis (Diago *et al.*, 2019). "VitiCanopy" App uses smartphones as imaging devices to measure vine performance attributes such as canopy vigour, LAI and porosity (De Bei *et al.*, 2016).

Pests and diseases

Grape cultivation in India faces serious threats from several diseases and insect pests. Major fungal diseases are downy mildew, powdery mildew and anthracnose, whereas, mealybug and thrips are major insect pests that cause enormous economic losses to grape cultivation. Among these, Downey mildew is one of the serious diseases in many horticultural crops (Somkuwar and More, 1996) including grapes. Use of appropriate pesticide in right dose at right time and right place holds the key for effective pest management.

Visual inspection of diseases and insect pests is time consuming, subjective, risky and expensive. Use of new sensors and monitoring tools has been shown to provide objective, rapid, cheap and reliable diagnosis of pests and diseases in vineyards (Lee and Tardaguila, 2021). These technologies have opened new frontiers to map disease/pest across vineyards in order to apply fungicides differentially using VRT technology (Chen *et al.*, 2020). Using computer vision and deep learning, Gutierrez *et al.* (2021b) could detect and differentiate downy mildew and spider mite in commercial vineyards.

Computer vision, hyperspectral imaging and machine learning have been applied for assessing downy mildew in grapevines (Rose *et al.*, 2016). Use of hand-held UV-LED fluorimeter for early detection of stilbenoid phytoalexins associated with Downey mildew infections on grape leaves was reported by Latouche *et al.* (2015). Wine producers set tolerance levels for diseases such as powdery mildew and Botrytis bunch rot. Two apps have been released (PMapp® and RotBot®) which allow users to quickly assess the severity of these diseases on clusters and calculate both the incidence and severity of the disease and also record other parameters such as date, time and geo-reference position (Hill *et al.*, 2014; Birchmore *et al.*, 2015).

Forecasting models and DSSs are valuable tools to manage biotic stresses in viticulture. During the last few years several computer-based disease and insect pest prediction models and decision support systems (DSS) have been developed in many crop plants including grapes. Rosa *et al.* (1993) developed PLASMO (*Plasmopara* Simulation Model) model for forecasting downy mildew in *Vitis vinifera*. The model simulates the development of downy mildew on the basis of climatic conditions.

Chen *et al.* (2020) developed an efficient and accurate machine learning algorithms for predicting Downey mildew that reduced at least 50% of fungicide use in Bordeaux region of France. Brischetto *et al.* (2021) developed a mechanistic model to predict secondary infections of *Plasmopara viticola* and their severity as influenced by environmental conditions. Powdery mildew caused by *Uncinula necator* fungus is another important disease of grapes. Fungal growth, conidia formation and germ tube formation are mainly influenced by temperature. Management strategy of Powdery Mildew disease on grapes by a decision support system based on weather and image processing was developed by Mundankar *et al.* (2007).

In warm tropical and sub-tropical conditions, anthracnose disease caused by *Colletotrichum gloeosporioides* affects tender shoots and young fruits reducing vine productivity and fruit quality. Disease incidence and severity have been shown to be dependent on weather parameters. Ghule *et al.* (2015) reported favourable weather conditions for development and progression of anthracnose. These were rainfall with minimum temperature between 22.33 to 23.12 ^{0}C, maximum temperature between 30.12 to 31.88 ^{0}C, RH-1 more than 67% and RH-2 more than 51%.

In India, major insect pests in grapes are mealybugs, thrips, flea beetle, leafhoppers, stem borer and mites in order of their economic damage to the crop. Indiscriminate use of pesticides not only increases cost of cultivation but also is harmful to the environment and human health. Therefore, pest management in viticulture should follow an integrated approach, including best agronomic practices, advance forecasting using models, decision support systems (DSSs), biological control agents and chemical sprays for reducing pesticide use (Pertot *et al.,* 2017). Chougule *et al.* (2019) developed a grape crop protection decision support system named as "PDMGrapes" using ontology, semantic web rule language and image processing techniques for management of insect pests and diseases on grapes in hot tropical region of India.

Lessio *et al.* (2021) have reviewed mathematical models and DSSs developed to predict key aspects of insect pests. These models are used for forecasting seasonal occurrence and spread of insect pests. Under integrated pest management (IPM), one of the most important components is the reduction in number of pesticide sprays and pesticide doses. Roman *et al.* (2022) developed DOSA3D decision support system that allows the dose to be adjusted to the specific scenario. DOSA3D calculates the optimal application volume rate by estimating the leaf area index and takes into account the overall spraying efficiency and the pest or disease to be controlled. DOSA3D could achieve pesticide savings up to 53% in fruit trees and 60% in vineyards.

Water status in vineyard

Current changing climates are characterized by water scarcity and higher temperatures; therefore, assessment of vineyard water status and irrigation management are becoming increasingly important. Thermal imaging technology has been used extensively to determine vineyard water status manually (Grant *et al.*, 2016) or remotely using aerial platforms (Bellvert *et al.*, 2014). Thermographic instrument can also be mounted to a ground-based vehicle for on-the-go mapping of vine water status in commercial vineyards (Gutierrez *et al.*, 2021a). Small thermal camera attached to a smartphone has also been used for assessing vine water status (Petri *et al.*, 2019). Recently, near infrared spectrometers mounted on mobile platforms have been used to assess vine water status in a stop-and-go mode (Diago *et al.*, 2017). A mobile phone application (ApeX-Vigne) has also been developed for monitoring vine water status in vineyards (Pichon *et al.*, 2021).

Yield components and crop forecasting

During harvesting of grapes, yield can be easily monitored by measuring the weight of berries flowing across load cells fitted to mechanical harvesters (Taylor *et al.*, 2019). Computer vision systems have recently been used to assess grape yields based on cluster compactness (Palacios *et al.*, 2019), number of berries per cluster (Aquino *et al.*, 2018), cluster weight (Liu *et al.*, 2020b) and berry size (Roscher *et al.*, 2014). Three android-based Apps viz., vitisFlower® (Aquino *et al.*, 2015), vitisBerry® (Aquino *et al.*, 2015) and 3DBunch® (Liu *et al.*, 2020a) have been developed for measurements of flower, berry and bunch parameters. For assessing large commercial vineyards, automatic RGB image capturing gadgets are mounted on mobile vehicles and yield predictions are made using computer vision technology (Palacios *et al.*, 2020).

In addition to these techniques, mathematical models are also used to predict annual yields in in many horticultural crops. Jaslam *et al.* (2022) used 44 years (1974-75 to 2018-19) vegetable production data to forecast vegetable production in the next five years starting from 2019-20 in UAE. For onions and green shallots, linear trend model was selected as the best fit, whereas, simple exponential smoothing model was most suitable in cauliflowers, broccoli, pumpkins, squash, gourds and spinach. The optimum model obtained for forecasting carrots and turnips was Holt's linear exponential smoothing model and ARIMA model was the best fit for the rest of vegetable groups.

Fruit composition and quality attributes

Near infrared spectral analyzers are capable of monitoring dynamic changes in berry composition during the ripening period and, therefore, provide an alternative option to destructive quality testing procedures. Portable near infrared spectrometers have been used for determining total soluble solids and other compositions in grape berries under both laboratory and field conditions (Barnaba *et al.*, 2013) This technology has also been successfully implemented on-the-go from a moving vehicle to monitor the dynamics of berry ripening in the vineyard (Fernandez-Novales *et al.*, 2019).

Another non-destructive technology consisting of hyperspectral imaging (HIS) to fingerprint the colour pigments of whole grape berries has also been developed for laboratory testing (Diago *et al.*, 2016b) and on-the-go from a mobile platform in the vineyard (Benelli *et al.*, 2021). A chlorophyll fluorescence-based sensor Multiplex® (FORCE-A, Orsay, France) has been developed for contact-free measurement of anthocyanin content in grape berries under laboratory (Ben Ghozlen *et al.*, 2010). These sensors can be mounted on harvesters for data acquisition on-the-go (Bramley *et al.*, 2011) Computer vision technology is also being used for sorting berries in many wineries before crushing. Vegetation indices derived from remote and proximal sensors were also used to evaluate quality characteristics of table grapes (Anastasiou *et al.*, 2018). Proximal sensing proved to be more accurate in terms of table grape yield and quality characteristics compared to satellite-based monitoring.

CONCLUSION

Choosing appropriate technologies for different types of application is important in precision viticulture. Though satellites and aircrafts are excellent tools for developing prescription maps for VRT machines, satellites have low resolutions and operational cost of aircrafts is high. In this regard, UAV platforms give high resolution, flexibility of use and economic feasibility. However, they can only monitor small areas. VRTs are well-developed and widely used, especially in chemical applications. Remote and proximal monitoring technologies and VRT machinery are being extensively used in some parts of the world, while robotics is in an experimental stage. In India, where majority of vineyards are small and fragmented, use of expensive precision technologies may not be feasible. However, at village/block/district level some of these technologies like UAV and proximal sensors can be adopted by farmers' cooperatives to make viticulture technologically, economically and environmentally sustainable.

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