Assessing berry number for grapevine yield estimation by image analysis:

case study with the white variety "Arinto"

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Dissertation to obtain a Master's Degree in

Viticulture and Oenology Engineering

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2020 - 2021

AKNOWLEDGEMENT

My name is Sergio Genuardi and I am a proud winemaker and viticulturist. Six years ago I started a path without knowing where it would take me, against all my expectations, I have always managed to reach the aim, first the three-year degree, now the master's. This concludes another splendid experience that has given me the opportunity to grow personally and professionally.

The time has come to say THANK YOU to all the people who made this possible and to the people who, along the way, accompanied, supported and motivated me.

Thanks dad and mom for allowing me to realize my dreams, motivating me continuously.

Thanks Paolo who, besides being a brother, a friend and an example.

I thank all my family for always giving me that extra motivation not to give up.

I am grateful to my roommates and fellow adventures: Andrea, Tito, Tony, Nicolò, Giuditta e Giacomino.

I am grateful to Rita for helping me set up and correct the English thesis.

I am grateful to Professor Carlos Lopes and Professor Antonino Pisciotta for their support in writing the thesis.

I am grateful to Gonçalo Victorino, for the continued support throughout the research work and for the patience in answering my countless questions.

I am grateful to all my old friends that supported me during all the years before arriving at this point.

A special thanks to all of you,

Sergio

ABSTRACT

Yield estimation in recent years is identified as one of more important topics in viticulture because it can lead to more efficiently managed vineyards producing wines of highly quality. Recently, to improve the efficiency of yield estimation, image analysis is becoming an important tool to collect detailed information from the vines regarding the yield. New technologies were developed for yield estimation using a new ground platform, such as VINBOT, using image analysis. This work was done in a vineyard of the "Instituto Superior de Agronomia", with the aim to estimate the final yield, during the growing cycle 2019 of the variety "Arinto", using images collected in three different modality: laboratory condition (1), field condition (2) and VINBOT robot. In the every condition, the images were captured with the RGB-D camera. For (1) and (2) the photos were acquired manually through the use of a digital camera placed on a tripod but in the (3) the RGB-D camera was fixed on the VINBOT robot. In this work, the correlation of yield components between field data and images data was evaluated. In addition, throught MATLAB, it was evaluate the number of visible berries in the images and the percentage of visible berries not occluded by leaves and by other berries. Througt the laboratory results was calculate a growth factor of bunches on the periods pea-size and veraison. On the VINBOT analysis the efficacy to estimate the total yield from the number of berries was higher at maturation with a 10% error ratio. The relationship between canopy porosity and exposed berries showed for all the stages high and significant R^2 indicating that we can use it to estimate berries occlusion through image analysis. This accuracy makes the proposed methodology ideal for early yield prediction as a very helpful tool for the grape and wine industry.

Key words: Algorithms, Image Analysis, MATLAB, Yield Estimation, VINBOT

RESUMO

Recentemente, novas tecnologias para estimativa de produtividade têm sido desenvolvidas usando sensores de imagem a bordo de plataformas terrestres, como o robô VINBOT. O presente trabalho tem como objetivo estimar o rendimento da cultivar branca 'Arinto' através do número visível de bagos contados nas imagens adquiridas em três estados fenológicos: bago de ervilha, pintor e maturação, na vinha experimental do Instituto Superior de Agronomia, em Lisboa. O trabalho utilizou imagens colhidas em três condições distintas: laboratório (1), campo (2) e pelo robô VINBOT (3). Com a ajuda do MATLAB, avaliou-se o número de bagos visíveis nas imagens e a percentagem de bagos visíveis (não encobertos pelas folhas e outros bagos). As relações entre dados reais (laboratório e campo) e dados obtidos nas imagens foram avaliadas. Em relação aos dados laboratoriais, a regressão entre o número médio de bagos visíveis e o peso do cacho, apresentou um R^2 = 0,76 na fase de bago de ervilha, R^2 = 0,92 no pintor e R^2 = 0,85 na maturação. A regressão entre o número de bagos visíveis nas imagens e o número total de bagos mostrou um R^2 = 0,83 no bago de ervilha, R^2 = 0,86 no pintor e um R^2 = 0,79 na maturação. Relativamente aos dados de campo, foi analisada a visibilidade dos bagos em diferentes níveis de desfolha e a relação entre a área dos cachos visíveis e o número de bagos visíveis em condições de videiras não desfolhadas. A percentagem de oclusão bago por bago foi de 49% na fase de bago de ervilha, 59,8% no pintor e 56,4% na maturação. Nos dados do VINBOT, a estimativa do rendimento produziu um erro de -18% no bago de ervilha, 27% no pintor e 10% na maturação. Esses resultados indicam que a metodologia proposta pode produzir uma previsão de rendimento antecipada, porém ainda é necessáriomais investigação para melhorar a precisão dos algoritmos.

Palavras-chave: Algoritmo, Análise de Imagem, MATLAB, Estimativa de Rendimento, Vinbot

RESUMO ALARGADO

A análise de imagens é usada em muitos procedimentos de avaliação de produção, particularmente na viticultura, para melhorar a organização das operações na vinha e adega. Este trabalho apresenta os resultados da estimativa do rendimento de uma casta branca denominada Arinto. A amostragem foi realizada numa vinha do Instituto Superior de Agronomia, na Tapada de Ajuda, Lisboa, durante o ano de 2019 pelo anterior grupo de estudos. Nesta tese, esses dados foram usados para estudar algumas variáveis necessárias ao cálculo da estimativa da produção. Foram utilizadas imagens colhidas em três condições distintas: laboratório (1), campo (2) e robô VINBOT (3), e em três estados fenológicos distintos, bago de ervilha, no pintor e maturação. Com a ajuda do MATLAB, avaliou-se o número de bagos visíveis nas imagens e a percentagem de bagos visíveis (não cobertos por folhas e outros bagos). Foram avaliadas as relações entre os dados reais (laboratório e campo) e os dados obtidos nas imagens. Dos resultados obtidos em laboratório, foram consideradas duas relações, a primeira entre a média do número de bagos visíveis e o número total de bagos, a segunda entre a média do número de bagos visíveis e o peso do cacho. Em condições de laboratório calculou-se o peso médio do bago, respectivamente 0,21 g ao bago de ervilha, 0,91g ao pintor e 1,37 a à maturação. O número médio de bagos visíveis contados nas imagens foi, respectivamente, 109 ao bago de ervilha, 87 ao pintor e 103 à maturação.

Quanto à percentagem de oclusão dos bagos por outros bagos, foi observado um valor de 49,1% ao bago de ervilha, 56,4% ao pintor e 59,8% na maturação. Através da análise das imagens captadas no campo, determinou-se a visibilidade dos bagos com diferentes níveis de desfolha. A análise de regressão entre porosidade da sebe e a % dos bagos visíveis, apresentou em todos os casos um coeficiente de determinação (R^2) elevado e significativo.

Em relação aos dados laboratoriais, a regressão entre o número médio de bagos visíveis e o peso do cacho, apresentou um $R^2 = 0,76$ ao bago de ervilha, $R^2 = 0,92$ no pintor e $R^2 = 0,85$ na maturação . A regressão entre o número de bagos visíveis nas imagens e o número total de bagos mostrou um $R^2 = 0,83$ no bago de ervilha, $R^2 = 0,86$ no pintor e um $R^2 = 0,79$ na maturação. Relativamente aos dados de campo, analisou-se a visibilidade dos bagos em diferentes níveis de desfolha e a relação entre a área dos cachos visíveis e o número de bagos visíveis. A percentagem de bagos encoberta com outros bagos foi de 49% na fase do bago de ervilha, 59,8% ao pintor e 56,4% na maturação. Nos dados do VINBOT, a estimativa de rendimento produziu um erro de -18% ao bago de ervilha, 27% ao pintor e 10% na madurção. Esses resultados indicam que a metodologia proposta pode produzir uma previsão de rendimento antecipada, mas mais estudos ainda são necessárias para melhorar a precisão dos algoritmos.

Palavras-chave: Arinto, Análise de Imagem, MATLAB, Estimativa de Rendimento, Vinbot

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% E = % Error

% Vb_b = % Visible Berries

2D = Two-dimensional

a* = Greenness-redness coordinate

AbO_b = Average berry occlusion by other berry

ABV = Average bunch volume

AbW = Average Berry weight

b* = Blueness-yellowness coordinate

bGF = Berry growth factor

Btot = Total number of berries

btot = Total number of berries

bW = Berry weight

BW = Bunch weight

CIE = Commission International d'Eclairage

CIELAB = Color space CIE L*a*b

FP = False positive

HSB = Hue, Saturation, Brightness

IF = Fruitfulness Index

ISA = Instituto Superior de Agronomia

L* = Luminance coordinate

LCM = Linear Canopy Meters

P = Porosity

RGB = Red, Green, Blue

ROI = Region of Interest

SMPH = Semi-minimal hedge pruning system

SPs= Smart Points

Tb_L= Total berries laboratory condition

Vb_B = visible berries at bunch level

Vb_L = visible berries laboratory condition

Vb_v = visible berries at vine level

VBA = visible bunch area

Vbtot = Visible berries with removal of all leaves

VSP = Vertical shoot positioning

Est.Y = Estimated yield

1. INTRODUCTION

The quality and the quantity of the grapevine production is determined by many factors, being the spatial variability an important issue that in precision viticulture assumes a growing importance. When we talk about precision viticulture we mean the set of all precision technologies that together with interconnected agriculture make it possible to identify problems, reduce and prevent diseases, improve production and working conditions (Matese *et al*., 2015). It is based on data (big data), software platforms, latest generation devices, monitoring and geolocation tools, the Internet of things (Matese *et al.,* 2015).

The determining factors of spatial variability are the microclimate, morphology of the territory (exposure, slopes), the characteristics of the soils and the phytosanitary state of the plants. Spatial variability is an essential element to consider, as it influences plant development, management practices and affects important parameters such as yield estimation.

Instead, the temporal variability of the agricultural environment is linked to the speed with which the physical, chemical and biological processes that act on the soils and the induction of new sources of anthropogenic variability occur.

Yield estimation has become a very important topic of study in recent years as researchers showed growing interest towards solving issues around spatial and temporal variability within a vineyard. Currently the yield estimation is carried out by laborious manual measurements, which can easily lead to errors due to incorrect and inappropriate sampling. That is what led to non-invasive proximal sensors, a kind of estimation that is object of study, since the 1980s, as it is a valid measure to reduce work times and workforce, favoring the objective acquisition of data.

It is useful to distinguish remote sensing, which includes all activities that involve observing and measuring the characteristics of an object or target from a long distance, to proximal sensing, which enables to monitor remote activities close to or in contact with what is being observed. In both cases, the commonly used sensors allow to carry out a study on an object by analyzing the behavior of its surface at different wavelengths, in various domains of the electromagnetic spectrum. Although much of the work done so far is promising, we have not yet reached the "vineyard of the future", for which these technologies can provide powerful tools to give the management the exact state of their vineyards (Seng et al., 2018).

Thus, the development and implementation of new and innovative techniques is a key issue in viticulture research to improve the sustainability and quality of vine production.

This study has the objective to create a glance of what can be achieved in the "vineyard of the future", considering images analysis acquired in the field and in the laboratory, manually and automatically, during 2019 at the ISA (Instituto Superior de Agronomia). This project has developed a methodology for estimating the initial yield, during the analysis of RGB images (red, green, blue), which will allow us to have essential yield forecasts for the organization of the agricultural year, such as, for example, the possibility of making alternate harvests based on the estimates obtained in the different parcels.

In this regard, we will also try to contribute to the improvement of the EU VINBOT algorithms, the autonomous cloud computing robot for vineyards that optimizes the management strategy of the yield and the quality of the wine funded under the PMI program FP7 (Lopes et al. 2017; Guzman et al., 2016 a).

AIM OF THE WORK

The main objective of this thesis is to count visible berries on previously collected images and use the data for yield estimation. Due to the global pandemic, which did not allow to do field work, our work will be based on the study of the Portuguese white grape variety "Arinto" using images and data collected by the ISA research team in 2019 . The relationships between visible berry number and actual yield in three different phenological phases will be analyzed

This work represents an effort to develop models to estimate yield and, specifically, an estimation of the berries that are occluded by leaves or other berries, to be able to conduct a yield forecasting of a vineyard as accurate as possible. Finally, the analysis aims to improve the algoritms used by the robotic platforms for yield estimation.

2. LITERATURE REVIEW

Vines are one of the most widely grown fruit crops in the world. The Vineyards cover a total area of 7.5 million hectares at a global level, producing a total of 75.8 million tons (OIV, 2018) which is the reason why, studies and research for new technology innovation, like yield estimation, are continuously carried out. For this reason, from the 1980s, the use of non-invasive proximal sensors has been increased, in order to reduce work times and workforce, favoring the objective acquisition of data. Thanks to new image analysis techniques, fast and reliable measurements can be obtained and, in recent years, numerous studies have shown how to apply these new technologies in viticulture.

The practical distribution of robotics in precision viticulture is still in the emerging phase, but many projects are already underway or in the final stages of development, and some have already been placed on the market. Examples of prototype robots in viticulture are VineRobot, VINBOT, VineGuard, VRC Robot, Forge Robotic Platform. As mentioned in the previous chapter, spatial variability influences plant development, management practices and affects important parameters such as yield. The application of these remote sensing technologies in viticulture has allowed to describe in high resolution the spatial variability in the field. These new technologies are part of robotics, remote sensing and wireless sensor networks. The new diagnostic-investigations allow to obtain qualitative and quantitative information on the object of the study. Remote sensing describes all activities that involve observing and measuring characteristics of a given object from a long distance, while proximal sensing consists in monitoring activities close to or in contact with the given object. In both cases, the commonly used sensors allow study an object by analyzing the behavior of its surface at different wavelengths, in various domains of the electromagnetic spectrum (Ahern, F. J. et al,; 1987). One of the most important challenges is the accuracy of yield estimates through grape detection in images. For wineries it is important to know in advance the quantity of grapes produced in order to predict and organize the purchase of new tanks, oak barrels, and wine products. Ultimately for companies it is important to be aware of the parameters that define the yield to be able to design a logistic plan and a strategy of production each year. An early estimate of yield can be achieved through image analysis techniques, counting the number of flowers per inflorescence or the number of berries per cluster (Hacking et al., 2019). Automating the analysis of yield determining components is important to both improve yield and efficiency, as current manual approaches do not satisfy the rapid measurement requirements. The manual sampling carried out immediately before the harvest has a margin of error that goes from 3 to 30% (Liu et al., 2017). Schöler et al. (2015) conducted research on cluster phenotyping image processing in the context of genetic programs, which included three quantitative analysis methods based on: berries, vertebral internodes and other internodes.,. Nuske et al. (2014) presented image processing methods capable of generating more reliable and unbiased estimates than manual estimating methods. We know that the number of berries remains almost stable after fruit set having a vital impact on the final weight of the bunch (Martin et al., 2003).The number and weight of the grapes per bunch are important parameters for obtaining early yield estimates,, our studies are mainly focused on the manual counting of the berries visible in images captured previously at the ISA (Instituto Superior de Agronomia) vineyards.

Vineyards do not present a uniform growing and do not have uniform microclimatic conditions (Boselli et al., 2016). This variability causes different vine physiological responses with direct consequences on grape quality and yield (Matese and Di Gennaro, 2015). It is necessary to know the pedological characteristics (structure, texture, depth, geomorphology, exposure) and the hydrogeological conditions to balance the production factors and differentiate quality of production (Boselli et al., 2016). The introduction of new technologies supporting vineyard management can increase the efficiency and quality of production while, at the same time, improving the economic and environmental sustainability (Boselli et al., 2016; Matese and Di Gennaro, 2015).

As mentioned in chapter one, in order to practice precision viticulture it is important to consider the differences due to spatial variability, in addition, another important parameter is the geodiversity, which can be permanent and temporary. Permanent geodiversity is determined by factors that do not change easily over time, such as the physical structure of the soil and subsoil while temporary geodiversity is determined by a constant modification of environmental parameters and the availability of nutrients to the crop (Boselli et al., 2016).

2.1. Monitoring technologies

The aim of the monitoring process is to obtain the maximum amount of information within the vineyard. Today, a wide range of sensors is available to monitor different parameters that characterize the plant growth environment and are employed in precision viticulture for remote and proximal monitoring of geo-localized data (Matese and Di Gennaro, 2015).

2.1.1 Sensing platform

Sensing platforms can be hand-held or mounted on fixed and mobile platforms, and able to position the detector in or over the area of interest. Examples of this kind of platforms are satellites, aircraft, helicopters, drones or terrestrial robots (Jones and Vaughan, 2010). Monitoring technologies can be separated into two groups: remote sensing and proximal sensing, depending on the distance from which they are being applied. Remote sensing includes aerial imaging while proximal sensing includes sensors deployed from a proximal distance to the analyzed object, similar the tools that will be used in this thesis.

2.2. Image analysis as a precision viticulture tool

Digital imaging (RGB or othertypes) is a powerful way to collect information and monitor crops with the assistance of automatic systems. As said in previous paragraphs, these images can be captured by satellites, drones, robots or other ground vehicles equipped with optical sensors. Digital images can be used to monitor crops in space and time, as they have the capability to describe several plants features that can be used to improve vineyard managing by informing the farmer regarding, for example, fruit quality and expected yield (Nuske *et al.,* 2011; Diago *et al.,* 2012a; Nuske *et al.,* 2014; Lopes *et al.,* 2016).

2.3. Yield estimation

The word yield refers to the quantity (weight) of fruit on a given spatial area, for example, tons of grapes per hectare. In some cases, it refers to the amount of fruit produced in a single vine. A precise forecast could lead to more efficient management of the vineyards and improvement of wine quality (Dunn *et al.,* 2004). As a matter of fact, accurate yield forecasting helps logistical planning, during and after the harvest; for example, it provides information on the volume of grapes that will be collected, in order to know in advance where the grapes will be stored and predict the market price (if grapes will be sold) (Cunha *et al.,* 2010). In this context, it is very important to know the phenology of the vine. As it is the basis for a good understanding of the vegetative-reproductive phenomenon of the plant and it allows a correct application of the non-invasive methods for estimating the yield.

The first typical phenomenon of the vine is the leaking of sap from pruning cuts, a consequence of a rapid increase in the radical absorption in beginning of spring as the temperatures are rising. About two weeks after the weeping there is the budburst, which includes a series of events that range from the swelling of the bud, to the consequent opening of the bud bracts and therefore to the spillage of the bud. Budburst in vineyards in northern hemisphere areas usually occurs around March/April, even though it depends heavily on external factors, such as temperature, endogenous factors and hormonal stimuli (Fregoni, 1998). From a hormonal point of view, the development of the root system, and consequently the budding, is regulated by the auxins and gibberellins produced by the leaves and, above all, by the cytokinins elaborated by the apexes of the roots themselves (Wang *et al.,* 2011).

The budding depends on the geographical area, in Europe it usually occurs from April to July, nevertheless, due to climate change, phenological phases are more irregular in their period. A phenological phase of the vine that goes through a very long period of time is that of the growth of the shoot. Also in this case there are important influences due to the environmental conditions, in particular to the temperature. Leaves, nodes, internodes, buds, clusters progressively integrate on the growing shoot. Simultaneously with the growth of the sprout there is the development of the cluster inflorescence. This culminates with the phenological phase of the flowering of the vine. Subsequently the period of predominantly cross-pollination occurs, carried primarily by the wind and subordinately by pollinating insects and, at last, flowers become fruits (fruit set)., Once the green grape has been obtained as a result of the fruit set, there is an increase in its organ's size which passes through three specific phases (berry growth, veraison and maturation) during which it goes through structural and composition changes. Fruit-set, veraison and maturation are the phenological phases that will be studied in this work, through the image analysis, to estimate the yield of a vineyard.

2.3.1 Estimation methods

There are several ways to predict the vineyard yield. The most common method used in commercial vineyards is the sampling and manual counting of yield components, as number of vines/ha, number of nodes/vine, number of shoot/node, cluster/shoot, flowers/cluster, berries/cluster, berry weight (Martin *et al.,* 2003).

2.3.1.1. Manual sampling of yield components

Manual sampling is based on the manual evaluation of the yield and is applicable in different phenological stages. Some of these samples are destructive and time-consuming. The size of sampling first depends on the variability in the field. However, greater is variability, greater is the number of samples requires. On other hand, the degree of samples accuracy is critical. Forecasting method can be used at a range of times during the season.

A very early yield forecast can be made estimating bud fruitfulness before budbreak (Clingeleffer et al., 2001). The authors proposed two the formulas (*Eq. 1 and 2)*:

Equation 1

$$Bud\ fruitfulness\ index\ (IF) = \ inflorescences\ per\ burst\ node \qquad \textit{(Eq.1)}$$

Equation 2

$$Yield\ \left(\frac{t}{ha}\right) = \left(\frac{IF\ season}{IF\ previous\ seasons}\right) *\ historical\ average\ yield \qquad \textit{(Eq.2)}$$

Clingeleffer et al., (2001), used the Merbein Bunch Count Method (Antcliff et al., 1972). That method provides an assessment of number of bunches per vine, information on total node number, percentage budbreak, number of shoots, number of fruitful shoots and percentage fruitful nodes.

Yield forecasting can also be made by estimating the number of flowers (Clingeleffer et al., 2001). This method is indirect, as it is based on alometric relationships between inflorescence length and flower number, and it allows an early forecast of berry number (before bloom). However berry number is dependent on the fruit set-conditions.

When made on flowering, forecast can be inaccurate. Indeed, vines will be subject to many factors until harvest including possible environmental hazards, however, if not, an early forecast can be extremely useful to the farmer. Results from the work of Dunn and Martin (2007) show that the number of primary rachis branches has the potential to detect large seasonal deviation of bunch weight from long term, but in this case, branch loss do not vary too much season to season. The relationships between the number of primary branches and number of flowers per bunch remain relatively stable within seasons. An estimation of bunch size based on the number of primary branches can improve yield forecasting made from six to eight weeks after budbreak (Dunn and Martin, 2007).

Another estimate of the yield can be made at the fruit set stage. At this stage it is possible to know not only the number of bunches but also the number of berries each bunch has (Clingeleffer et al., 2001). Dunn (2010) proposed a forecast based on berry counts after fruit set. In this case the forecast should be made when the berries are at “pea size stage”. For the author the formula to use is the following *(Eq. 3):*

Equation 3

(Eq.3)

$$Yield\left(\frac{t}{ha}\right) = \#.vines * \frac{\#bunches}{vine} * \frac{\#berries}{bunches} * \frac{weight}{berry} * harvest\ efficiency$$

The formula intends to include the number of vines, the number of bunches/vine from bunch counts, the number of berries per bunch through sampling bunches, predicted average berry weight (at harvest) and lastly harvest efficiency. This forecast based on berry counts after fruit set can expect an error around 10 to 15% (Dunn, 2010). Yield predictions can be attempted at any time during the growing cycle of the vine, but logically they become more accurate close to the harvest. For that the veraison stage can be a good time to predict the yield. Just like the previous stage forecast models, for estimating the yield at veraison it is possible to use historical data and a berry growth factor. However, at this stage, the bunch is already well developed.

Using the formulas from Clingeleffer et al., 2001, which uses the berry growth factor, it is possible to predict the final yield *(Eq. 4 and 5):*

Equation 4

$$Bunch\ weight\ harvest = Bunch\ weight * berry\ growth\ factor \qquad \textit{(Eq.4)}$$

Equation 5

$$Berry\ growth\ factor = \frac{cluster\ weight\ at\ harvest\ (historical\ data)}{cluster\ weight\ (veraison)} \qquad \textit{(Eq.5)}$$

Manual sampling usually takes place between veraison and ripening, at which time the yield assessment may be ideal because all growth stages of crop development have occurred and the estimate should be more accurate. An accurate yield estimation near the harvest can still be very powerful, as it will help managing the harvest itself and all the logistics related to it. It can also be an effective way to improve wine quality by segmenting the harvest with the resulting prescription maps. Clingeleffer et al., (2001), proposed the following formula showed in *Eq.6:*

Equation 6

$$Yield\left(\frac{t}{ha}\right) = \frac{average\ yield}{vine} * number\ of\ vines \qquad \textit{(Eq.6)}$$

2.3.1.2. Airborne pollen model

At flowering stage, yield forecasting can be made using airborne forecast models. This model is valuable tools for the yield estimation because it put simultaneously several factors that influence the crop production: pre-flowering conditions, plant vigour and health. (Besselat and Cour, 1996).

However, this method is not very precise, since it detects the pollen of all the crops that are close to the area of interest.

This can be explained with several studies. One of this was conducted in San Michele all'Adige in Italy. The researchers used the Hirst-type sampler, which permits the determination of daily airborne pollen concentrations (P/m3/day), instead of a Cour trap, usually adopted in this type of research (Cunha et al., 2003). For a better result, the concentration of pollen was collected for five years, and it was also recorded meteorological parameters, which improve the model. Specifically, it was useful to record rainfall during the main pollen season, the phase preceding pollination, because rainfall can influence, negatively, the beginning of the pollen season (Cristofolini and Gottardini, 2000).

In another study, Cunha et al., (2003) used the Cour trap for the concentration of airborne pollen. In this method, pollen grains are trapped on vertical gauze filters with an area of 400 cm3 fixed vertically on a wind-vane, which continually orientates the filters according to the wind (Cour 1974). In this case during the flowering the filters are exposed for 3 or 4 days in the air. Airborne pollen is express in number of pollen grains transported per m3 of air. The model shows good results in crop prediction, but the main disadvantages of this forecast are the placement representative of the airborn pollen sampling device at regional level and complex laboratory process involved (Cunha et al., 2003).

2.3.1.3. Trellis tension method

In a work from Blom and Tarara, (2009), it has been seen that the trellis tension can be used for the yield monitoring. The trellis tension monitor was developed using the tension of the horizontal support wire of trellis. In order to predict the yield of the current year it is needed to consider the yield from an antecedent year, the trellis wire tension of the antecedent year and the wire tension of the current year. A greater number of data from the past years is necessary to improve the estimation of the yield, but the study demonstrate that the incidence of errors in the use of TTM is equal or a little bit lower than the traditional method.

2.3.1.4. Agrometeorological models

Agrometeorological models are obtained from the regression between climatic variables measured in a determinate phenological phase. These models assume that the climatic conditions are the main factor of the variations of the yield. According to Gommes, (1998), these models can be obtained through descriptive methods, regressions or yield simulations. The regression models use the main important climatic variables, such as air temperature and precipitation. The harvest simulation, describes the crop behaviour basing on the meteorological conditions which it is subjected to. These models are very variable and difficult to extrapolate, for that they are less used in yield forecasting (Samà, 2019).

2.4 Image analysis

The development and application of new and innovative techniques, like analysis of RGB images, with the objective of monitoring the vineyard is a key issue in viticulture research to improve grape-growing sustainability and quality of the production. However, the performance of a computer vision system only based on colour information depends on many factors that must be taken into account and studied (Diago et al., 2014).

2.4.1 Colors space

A color space is the combination of a color model and an appropriate mapping function of this model. In fact, a color model is an abstract mathematical model that describes a way to represent colors as codes of numbers, typically as three or four values called color components. Visible spectral information can be represented in different ways, also known as colour spaces. The most known and commonly used are the RGB (red, green and blue), the HSB (hue, saturation and brightness) and the L*a*b* (also known as CIELAB) (Samà, 2019).

2.4.1.1 RGB

Colour can be described in the RGB system. The RGB is a mixture of the spectral of the three colours red, green and blue. In digital image the range of RGB values is from 0 (darkness) to 255 (whiteness). In the electromagnetic spectrum the red, green and blue correspond to range between 700nm, 546nm and 436nm respectively. The system is formed by a cube comprising orthogonal RGB Cartesian coordinates *(Fig.1)* The combination of these three colour can produce all type of colour (Rossel *et al.,* 2006).

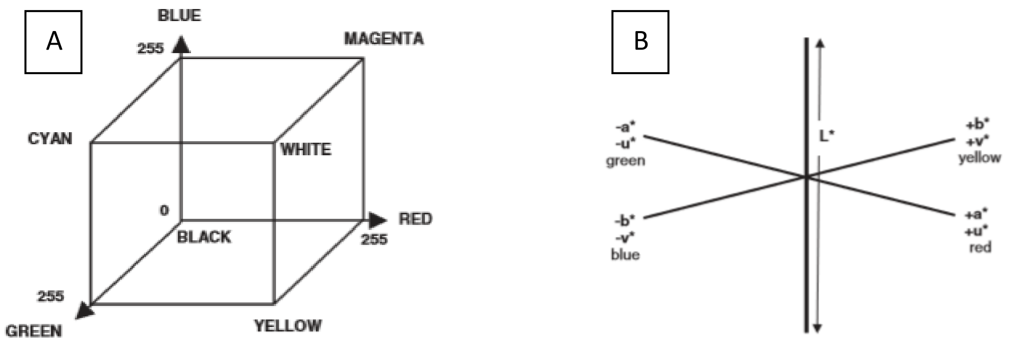


*Figure 1 The RBG model (A), the CIELa*b* colour space model (B) (Source: Rossel et al., 2006).*

2.4.1.2 HSB

In the HSB *(Fig.2)* (hue, saturation, brightness) the colour is specified in terms of three quality, hue (H), saturation (S) and intensity (B) (value or brightness). Hue is the actual colour, measure in angular degrees counter-clockwise around the the cone starting and ending at red = 0° or 360°. The HSB be represented by the circle. Around the perimeter there are the saturated colour. The central point represents white, formed by mixture of all colours. The intensity can be white at the centre of the circle and black at the base of the cone. The surface of the cone thus formed represent the saturated colours of different intensities (Jonas and Vaughan, 2010).

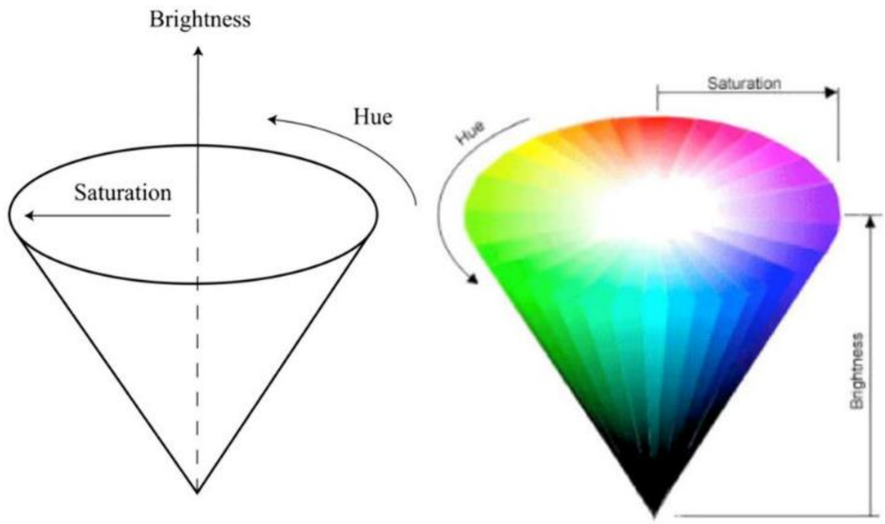


Figure 2 This scheme explain and describe the HSB color spaces.

*2.4.1.3 CIEL*a*b**

The last method is CIEL*a*b* Other method to describe the colour is the CIELa*b* space (Fig.1B). This system is obtained after the x,y,z coordinates which are transformed to a uniform chromaticity scale. In this system L is the metric lightness function which ranges from 0 (black) to 100 (white), the coordinate a* is from green to red, respectively –a* and +a*; the coordinate b* is from yellow to blue, respectively +b* ad –b* (Rossel *et al.,* 2006).

2.4.1.4 Traditional and machine learning approaches to image analysis

The traditional approaches to image segmentation is typically used to locate objects and boundaries in images (Tan, 2016) employing handcrafted heuristic criteria (e.g., intensity and colour distributions) to identify appropriate image, and deepen convolutional neural networks (CNNs), which is an evolution of the standard neural network (NN), allowing learning descriptive criteria of the desired image regions just from the image data itself (Rudolph et al., 2018).

Neural Network (NN) is an algorithm of the Machine Learning discipline that makes a computer able to mimic the functioning of the human brain in order to learn from experiences and predict a result starting from certain boundary situations (Anne Bonner 2019). This allows to have a tool that plays, in complete autonomy, roles that were previously intended exclusively for human like driving a vehicle or diagnosing a disease, NN represent a huge step forward in image recognition (Anne Bonner 2019). CNNs used for image classification classifies complete images and generally follow a common structure that shows two phases. The first is the feature extraction phase, in which multiple convolution layers and pooling layers generate successively more complex class characteristic image features (in the convolution layers) thereby down sampling the image size (in the pooling layers). The other phase concerns the classification, multiple fully connected layers derive class labels based on the derive image feature (Rudolph et al., 2018). CNNs have established themselves as a state-of-the art method for many tasks of image processing, including image classification (Krizhevsky et al., 2012) as well as, more recently, image segmentation (Long et al., 2015; Ronneberger et al., 2015).

2.5 Image analysis for grapevine yield estimation

As previously mentioned, the most commonly yield estimation methods described above are destructive, laborious, time-demanding and expensive. In recent years several studies have based their work on image processing in order to assess the yield estimation or other features of the vineyard canopy. The technology of image analysis allows the development of systems capable of estimating yield non-invasively in a fast, repeatable and accurate way (Diago *et al.,* 2015). The acquisition of the image on the field can be done manually (Diago *et al.*, 2012), or with modified agricultural vehicles such as robotic platforms or other ground vehicles. The digital image (RGB or other) is an effective way to collect information and monitor crops with the assistance of automatic systems for their analysis; these images can come from satellites, drones, robots or other land vehicles with optical sensors. Digital images can be used to monitor crops in space and time, with the ability to describe different characteristics of plants that can be used to improve the vineyards management by informing the farmer about, for example, the quality of the fruits and the expected yield (Nuske *et al.,* 2011; Diago *et al.,* 201a2; Nuske *et al.,* 2014; Lopes *et al.,* 2016).

One of the first works about image analysis, from Dunn and Martin (2004), had the aim to detect differences in visible characteristics between fruit and other elements of grapevine canopies. This work showed that fruit can be distinguished from other part of the canopy by image analysis and the fruit pixels could be counted, giving a quantitative measure of the amount of visible berry in each image (Dunn and Martin, 2004). More works are made by taking as yield components flowers (Diago *et al.,* 2015; Rudolf *et al.,*2018), berries or bunches (Tardáguila *et al,* 2012; Nuske *et al.,* 2014; Herrero-Huerta *at al.,* 2015; Aquino *et al.,* 2017).

2.5.1 Shoot detection

Zabawa *et al.,* (2019) found that different trellis systems influence the yield estimation, since the effectiveness of the work that will be done through the images analysis depends on them. In vertical shot positioning system (VSP)the grapes are positioned mainly on the bottom of the canopy and are often not very occluded. The semi-minimal hedge pruning system (SMPH), also called hedge quarter notes, has multiple branches and leaves. The grapes grow throughout the plant, often even inside the canopies, so this causes an occlusion. Both systems are challenging in berry detection and quantification. For SMPH, the estimated yield with the number of berries may not be sufficient due to the irregular arrangement of the berries (Zabawa *et al.,* 2019). Zabawa *et al.,* (2019) develops a robust pipeline detection that detects individual berries in images by defining a classification task of three classes and applying a completely twisted neural network. Furthermore, this work allows to investigate the size of the berries that could be useful for a even better yield estimate (Zabawa *et al.,* 2019). For this reason, the "berry", "border" and "background" classes will be defined, where the use of the "berry" and "border" classes allows the differentiation between the individual berries within a bunch. This detection allows the counting and identification of the position of each berry, but also the possible investigation of another important phenotypic trait, the size.

Hence, the algorithm has applicability in field scenarios and the potential to speed up and improve the accuracy of yield estimates for farmers using smartphones. In addition, by combining with existing work on flower counting (Liu et al., 2018; Aquino et al., 2015; Grimm et al., 2019), there is the possibility of an efficient determination of fruit set ratios on a large scale.

2.5.2 Flower detection

As said previously, the number of inflorescence and the number of flowers are important yield components to estimate the yield, because the flower become berries. Counting the flower number per inflorescence is essential for accurate assessment of fruit set. To improve forecasting quality, in recent years, several studies were based on the use of image analysis on inflorescences in order to predict the yield in early stages (Diago *et al.,* 2014, Aquino *et al.,* 2015; Millan *et al.,* 2017). Diago *et al.,* (2014) used RGB images taken under field conditions to estimate the number of flowers per

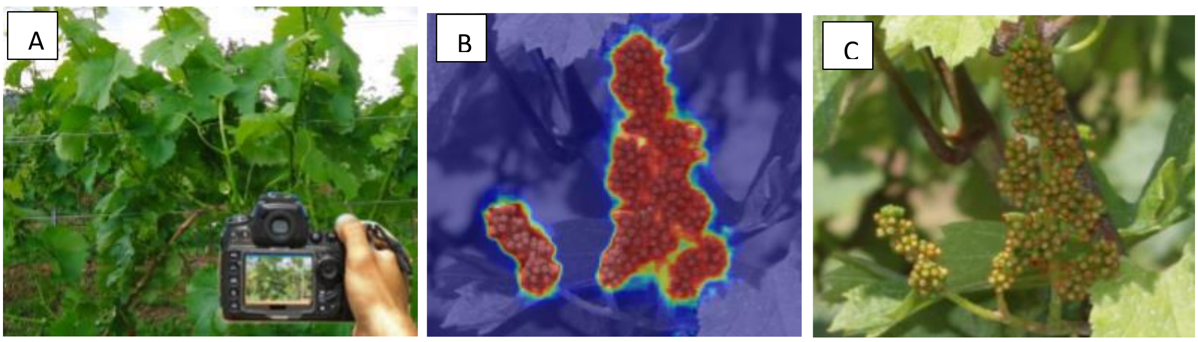


Figure 3 Workflow of flowers detection: Data acquisition (A), segmentation of images into 'inflorescence' and 'non-inflorescence' (B), flower extraction (C). (Source: Rudolph et al.,2018).

inflorescence and processed the images using MATLAB (MatlabR2010b, MathWorks, Natick, MA, Usa). The method developed for flower counting was fully automatic and involved three stages. The images were pre-processing involving conversion of the image from RGB to CIELAB color space, and an initial segmentation by means of threshold, separating by background from the flowers; in the second step there are the flower counting, and as the flowers present a higher degree of light reflection, the flowers corresponded to brighter areas; the last step consist to remove material other than flowers background from the flowers. The flowers present a higher degree of light reflection from the brighter area selected. The authors validated the results from the software, counting manually the flowers number and comparing that data by software. Other authors, such as Rudolph *et al.,* (2018), had a different approach to estimate the number of the flowers. They estimate the flowers number took by the images in field conditions, without background. The work was divided into four steps. The first consist in simple-to-handle image taking with camera; the second consist in identification and localization of the inflorescences with segmentation of the images; after the extraction of the flower; finally evaluation of resulting phenotyping data. The *Figure 3* show the workflow for flower detection.

Nowadays studies are trying to make easier the flower detection for yield estimation. Aquino *et al.,* (2015) started a study for a new Android application, vitisFLOWER ® for flower automatic counting.This is a non-invasive method applicable directly in the vineyard, which allows to count the number of flowers and the inflorescences of the vinewith a simple click. The application, called vitisFlower ®, first guides the user to take the photo using the smartphone's camera, then, by analyzing the images, detect and count the flowers (Aquino *et al.,* 2015). VitisFlower ® was developed for Android devices and uses OpenCV libraries to maximize computational efficiency. The application was tested on 140 inflorescence images of 11 vine varieties taken with two different devices. An accuracy of 94% was found (Aquino *et al*., 2015). The image analysis algorithm included in vitisBerry is based on mathematical morphology and classification of pixels by expected learning. As a prerequisite, the photo to be viewed must be expected by placing a dark background behind the cluster.

2.5.3 Berry detection

As described in the previous chapter 2.5, the number of berries is one component involved in the final yield determining the cluster compactness, cluster architecture and degree of berry aggregation (Cubero *et al.,* 2015) . Many works explained how to count the berries by image analysis. Grossetete *et al.,* (2012) used a digital camera and a simple Smartphone, from flowering to veraison. The photos were made using camera with integrated flash, as the berry surface reflects the light and the maximum point of reflection was on the center of the berries. The images were processed as following: the correlation between the Gaussian profile and the neighbourhood of each pixel was computed and the results obtained was summarized in a correlation map. The last step consisted in a morphological dilation in order to solve the situation where specular areas could occur on a single berry. At the end of the process, the authors obtained the number of visible berries. Diago *et al.*, (2012), used RGB images took in the field to assess leaf area and yield estimation. For the algorithm development, Mahalanobis distance was used. The Mahalanobis distance seems to be the most suitable and widely used model for pattern recognition and data analysis (Son *et al*., 2010). The Mahalanobis colour distance standardizes the influence of the distribution of each feature considering the correlation between each pair of terms (Al-Otum, 2003). In the experiment by Diago *et al., (*2012) the vines were randomly chosen and defoilated and cluster thinned in several steps. The pictures were made before and after any defoliation and cluster thinning. To avoid confounding effects from background and no artificial illumination, a white background was placed behind the canopy. The method processed a set of images and calculated the areas (number of pixels) corresponding to different classes like grapes, wood, background and leaf. Each one was initialized by the user, who selected a set of representative pixels for every class in order to induce the clustering round them. For the Algorithm validation, it was manually performed, selecting ROI (region of interest) on images that showed representative conditions of illumination and colors; the number of pixels for each class was manually counted. The segmentation results showed a performance of 92% for leaves and 98% for clusters, allowed to assess the leaf area and yield with R^2 values of 0.81 and 0.73, respectively.

In the Nuske *et al.,* (2014) develop an algorithm to detect the berries to known the final yield. They used a RGB camera and an artificial illumination mounted on a tractor. Their approach was to detect candidate hypotheses of where grape may be located in the images. To detect the potential berry location they used two ways, radial symmetry (Loy and Zelincky, 2003) which uses the circular shape of berry as a cue for detection; and the search of the maximal point of shading in the center of the grapes, illuminated by the flash. The next step of their algorithm was to classify the detected key points into grapes or not-grapes. The authors manually defined the berries center, that corresponded to positive, examples, of the appearance of berries and they removed bunches that were smaller than an area threshold by detections. Then they took measurements of the berries and made an estimating of fruit yield, evaluating the visible berries and berries self-occluded. After that, they implemented other two ways; in the first, they took convex hull formed by all the visible berries in the bunches; in the second, they took the size of a bunch using a 3D ellipsoid model. The authors, in the laboratory environment, collected images from ripe clusters, weighed and counted berry number. Initially they compared the total berries counted (manually) of each cluster against its weight, after, the visible berry count started by ellipsoidal model - the authors reported a lower correlation than for the visible cluster. Ellipsoidal model does not assume that the clusters do not have uniform density or the clusters are not ellipsoidal. Subsequently, the authors compared their automated berry counts whit the harvest crop weights (Nuske *et al.,* 2014).

Others works were also performed to estimate the yield, using 3D images. From a 2D image took from the field of bunches, it is possible to produce a 3D image, to detect the bunch weight and number of berries. The work performed by Herrero-Huerta *et al*., (2015) has the aim to remove the subjectivity deriving from the spatial and temporal variability of the grape production. For this type of work, there were some difficulties, such as having only the visible side of the bunch or having to deal with the occlusion and geometrical complexities of the bunches themselves. In that case the image acquisition of elements such as their position (spatial and attitude), was important, as it could have influenced the final accuracy (in term of prospective ray intersection) and completeness in terms of overlap between image of the 3D. To reconstruct the bunches in 3D model, the images were processed with Photogrammery Workbench, a software developed by the authors (Herrero-Huerta *et al.,* 2015).

Aquino *et al.,* (2017) also used 2D image analysis to estimate the number of berries per bunches. The authors divided the work into two steps, they extracted a set of berry candidates from the image by means of a morphological filtering, the bright spots produced by the light reflection on the berries surface were detected by finding regional maxima illumination; in a second time, the candidates not corresponding to berries, called false positive (FP), were discarded. The images were converted into CIELAB colour space (CIE 1976 L*a*b*) (Connolly and Fleiss. 1997). To obtain the berry candidates, the authors used a dark background, as it allows an easier extraction of a region of interest (ROI) by means of colour discrimination. The ROI was extracted from the image by thresholding of the channel b* using the Otsu's thresholding method (Nobuyuki, 1979). The ROI included also errors, other components, such as rachis which were deleted with filtering. The filtering process was carried out by means of pixel classification. In the second step of this work, the researches removed false positives. The components that corresponded to false positive were manually labelled in red color. After that, they used the Neural Networks (NN). Image classification is the process of acquiring an input (such as an image) and issuing a class (such as "berry") or a probability that the input is a particular class ("there is a probability of 90 % that this input is a berry "). It was created by assigning the value 0 and 1 to the red and blue components, respectively. NN produces real values that are required to obtain a classification result by assigning the values 0 and 1 to false and true positive. The authors considered that the values produced by the NN for each connected component were used to create a probability map in form of an image. Then, the new image was binarized using the threshold automatically provided by Otsu's method (Aquino *et al.,* 2017). The *Figure* 4 shows an example of these application of the whole described methodology step by step.

Artificial neural networks (NN) was used also in Behroozi-Khazaei and Maleki's study (2017) to develop an algorithm that could segment bunches.

The photos were made in a plant cover by leaves and near harvest. The authors obtained the 99.4% accuracy for their algorithm.

Furthermore, the algorithm was applied to yield estimation and found to have an error between 3% and 16% when compared directly to measured tons at harvest, using automated shoot counting (Liu et al., 2017) and to the berries per shoot method (Whitty et al., 2017).

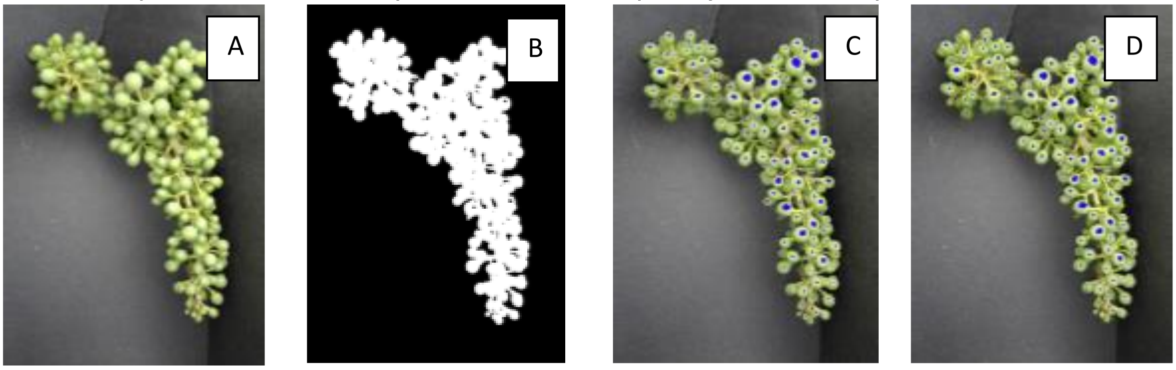


Figure 4 Example of the application of the methodology for berry segmentation. Original RGB image (A), ROI extracted (B), Berry candidates (C), Final result obtained after filtering false positive (D) (Source: Aquino et al., 2017).

Zabawa *et al*. (2020) presented a novel berry counting approach able to detect and mask single berry objects with a semantic segmentation network by using a class 'edge' to separate single objects from each other. This enables the evasion of the time and computationally intensive use of an instance segmentation network like the Mask-RCNN. With this method it is possible to handle two training systems with different characteristics and challenges (VSP and SMPH). Furthermore, unlike the other methods, the Zabawa et al (2020) approach can be inferred in minutes. The comparison with a classical regression approach yields results are just slightly worse than this new approach (R^2 = 97.19% for the VSP and R^2 = 92.20% for the SMPH). But the advantage of this new method is the potential extraction of additional phenotypic traits like the berry size. Despite these encouraging results, there is further space for improvements (Zabawa et al., 2020).

Liu *et al.* (2020) paper has presented a novel and fast algorithm which is able to count berries and estimate the 3D structure of both red and green grapes in-field from pea-sized to harvest development stages from a range of bunch architectures (Liu et al., 2020). Using only a single image from a smartphone and no calibration or prior information, the accuracy of the method was 89% when directly compared with the number of berries on a bunch. Instead, when averaged across 50 to 80 images, the accuracy improved until 99%. The algorithm was found to be robust to different bunch architectures qualitatively as well as give consistent results from pea-sized to harvest development stages. The rapid processing time of 0.1 s per image is dramatically faster than manual counting and faster than existing approaches in the literature as well as requiring no human interaction once the image has been captured (Liu et al. 2020). When the proposed method was used to estimate bunch weight, an accuracy of more than 92% was found on average over several dozen bunches in each dataset (Liu et al. 2020).

2.5.3 VINBOT Robot platform

Some of the previous works used a mobile land platform to collect images. In recent years, efforts have been made to anticipate the yield estimate by a few days before the fruit set, acquiring photos manually with artificial lighting (usually at night) or with the use of a mobile land vehicle at a speed of 5 km/h. Similarly, Nuske et al., (2014), in another study, used a tractor, which moved at a speed of about 5 km/h, equipped with an RGB camera and lighting to capture images in the vineyard at night. A classifier for berry detection has been developed which is fed with a large set of descriptors (over 30), color and shape (Nuske *et al*., 2014). The VINBOT *(Fig.5)* is a robotic platform that carries several sensors developed for vineyard monitoring (Lopes *et al.,* 2016). The platform can carry up to 65 kg and navigate on steep slopes.

Figure 5 View of the Vinbot platform in action in natural field conditions.

It is equipped with an ROS Indigo and Ubuntu 14.04 and carries a Kinect v2 RGB-D camera to collect RGB images. It also carries two 2D range finder lasers, one for navigation and one for canopy shape data.

- A robotic platform: mobile, durable with open-source software
- Color camera: RGBD Kinect to take images of the vine
- 3D range finders to obtain the shape of the canopy and to navigate in the field
- A Normalized Difference Vegetation Index (NDVI) sensor to compute the vigor of the plants
- A small computer for basic computational functions connected to a communication module
- A cloud-based web application to process images or to create 3D maps

- User friendly HMI to define navigation and data acquisition missions (Reyes and Sastre, 2016; Lopes et al., 2017)

3. MATERIALS AND METHODS

Given the historical period due to COVID-19, we were unable to carry out the necessary surveys previewed for the normal thesis. For this reason we have analyzed images and data obtained in 2019 thanks to a large study carried out by the ISA research group.

3.1 Localization experiment

As mentioned before, our data set is part of a big campaign which was carried out in 2019 in an experimental vineyard, in the Instituto Superior de Agronomia (ISA), in Tapada da Ajuda, Lisbon (38 ° 42'26.6 "N 9 ° 11'05.2" O) (*Fig.6*).

Figure 6 Tapada da Ajuda, Lisbon (38 ° 42'26.6 "N 9 ° 11'05.2" W), Instituto Superior de Agronomia (ISA).

This vineyard was planted in 2006 with the following varieties: Alvarinho, Arinto, Moscatel de Setubal and Viosinho grafted on rootstock 1103 Paulsen (*Vitis berlandieri* X *Vitis rupestris*) and Encruzado, Macabeu and Moscatel Galego grafted on rootstock 110 Richter (*Vitis berlandieri* X *Vitis rupestris*). It has an area of 1.46 ha, the distance between the plants measures 1 m and the distance between rows 2.5 m determining a plant density of 4000 plants/ha.

The rows are oriented North/South and east exposed caused by a slight slope (maximum of slope is 9%). This research thesis is focused on the *Vitis vinifera* L., variety Arinto which is planted from the 50th row to the 68th rows in an total area of 0.38 ha. The vines are trained to a vertical shoot positioning and spur pruned on a unilateral Royat cordon. The soil of the vineyard is a clay loam with

1.6% organic matter and a pH of 7.8.-7 (Teixeira et al., 2018). It is described as a reddish-brown clay, not basaltic limestone. The expandability and the field capacity values are high with a high usable capacity in the first 50 cm. The vineyard is drip irrigated and standard cultural practices in the ISA vineyards were applied to all the Arinto plot. The climate in Lisbon is classified Csa (C: warm temperature; s: summer dry; a: hot summer) as established by the classification of Köppen and Geiger (Kottek et al. 2006), with higher precipitation in the winter than in the summer. The annual mean temperature is 15.4 °C and the annual mean precipitation (1973 to 2000) is 725.8 mm (IPMA, 2019).

3.2 Studied variety

Vitis vinifera L., variety Arinto is also known as Pedernã in the region of Vinhos Verdes. Arinto is a variety with low fruitfulness but very large bunches, features that allow to compensate for the low number of bunches (Eiras-Dias et al., 2011):

- The budbreak is late;
- The shoot *(Figure 7A*) has a completely open extremity and a high density of creeping hairs. It presents an erect habit, a medium vigor, medium fertility of basal buds and a weak intensity of anthocyanin coloration of the buds (Eiras-Dias *et al;* 2011).
- The cluster is shown in *Figure 7B* is long, with conical shape and presents 1 or 2 wings; it has a medium level of compactness and a high weight. The berry has a rounded shape and medium size. The pulp is colourless and little hard (Bonaria, 2019);
- The young leaves have the upper edge colored in bronze. The adult leaf shown in *Figure 7C* presents a big and irregular profile; the margin is characterized by convex teeth of medium length and a medium level of swelling. The petiolar sinus presents overlapping lobes in brace form. The underside of the leaf is characterized by a medium-high density of hair (Eiras-Dias *et al;* 2011).

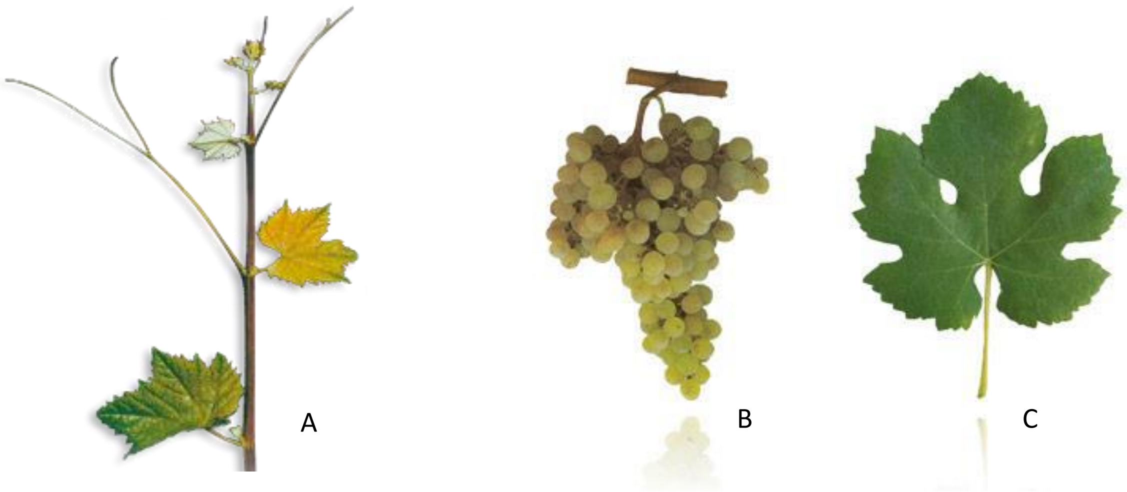


Figure 7 Picture of sprout (A) (Antunes et al., 2011), bunch (B) and leaf (C) of Arinto (www.vinetowinecircle.com).

3.3 Experimental design

In 2019, four rows (52-56-60-65) of 25 meters in length were selected in the vineyard for data collection in order to understand as much as possible the variability present in the vineyard. These canopy segments were called smart points (SPs) and were divided as shown in *Figure 8*. Ten meters (highlighted in red) were dedicated to collecting images with Vinbot throughout the growing season; 15 linear canopy meter (LCM) where to dedicate to the collection of images with Nikon RGB camera for three phenological phases: 5 LCM (highlighted in blue) for the pea size, 5 LCM (highlighted in green) for the veraison and 5 LCM (highlighted in yellow) for full maturity (Bonaria, 2019). The LCMs dedicated to the Vinbot sessions were set up with a meter scale (divided into 10 cm steps) fixed to the vines, to ensure that the same vine references are captured in the images throughout the season (Bonaria, 2019). The LCM dedicated to Vinbot sessions were set with a meter scale (divided into steps of 10 cm) fixed to the vines, to ensure that the same vine references are taken in the images throughout the whole season (Bonaria, 2019).

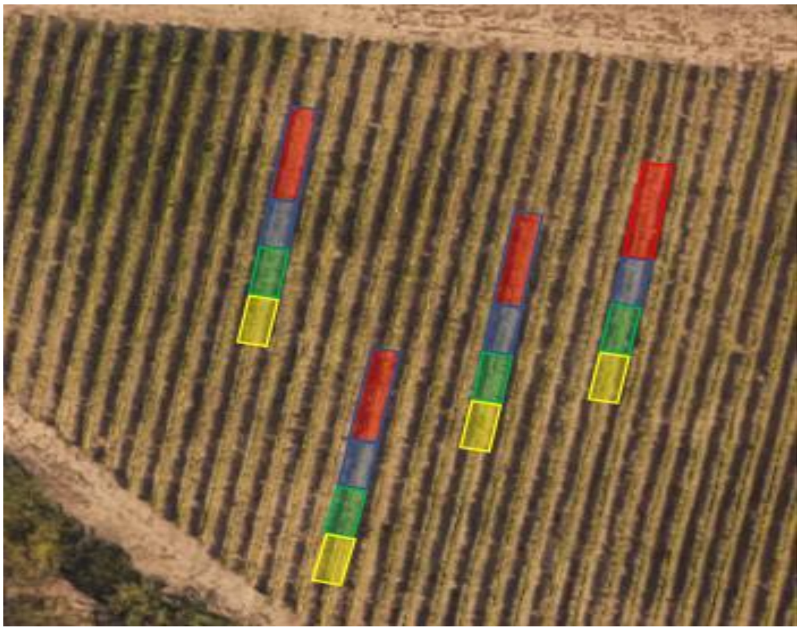


Figure 8 Rows (n° 52-56-60-65) chosen for the location of the 4smart-points, and the relative 10 and 5 meters where we collected the data: (red) 10m for the Vinbot sessions; (blue) 5m for pea size; (green) 5m for veraison; (yellow) 5m for full maturation. (Source Bonaria 2019).

3.4 Detailed measurements

Data illustrated in this paragraph used for the current thesis has been obtained in 2019. The berries clustered per smart point, meter and layer, were counted and weighed. The other bunches coming from the chosen LCM were individually labelled and inserted into aluminum containers. Using a computer for data input they were assessed in detail by the following proceedings:

1. Two images per bunch were collected with blue background using the same Nikon camera used in the field. To maintain the same distance from the bunch, the camera was mounted on a tripod. The

bunches were hung on a bar with the use of a metal spring paper clip tied to the bar in a precise point designated with two black marks made with a permanent marker.

2. Cluster weight was measured using a digital table scale (KERN FCB version 1.4).
3. Cluster volume was assessed using the water displacement method. A volumetric cylinder (NORMAX 1000:10 ±10) was filled to a certain level with water. The level of the cylinder was taken once more after the insertion of the cluster (Bonaria, 2019). The subtraction of the initial volume of water to the final volume obtained after the bunch insertion gives the corresponding volume of the bunch.
4. Berry weight was measured;
5. Manual calculation of the number of berries: to avoid contacts that would have given problems in the subsequent phase of image analysis, the berries for every bunch were distributed in casual order on the table making sure that they were spaced from each other. The berries, well distributed on the table in presence of the corresponding bunch label were photographed using automatic exposure control and flash with the SONY digital camera model DSC-H90 (manualslib, 2019b). The camera was fixed on a support to maintain the same distance from the table to guarantee the same scale in the each image analyzed.
6. Through the use of a MATLAB calculation program, a count of the berries visible on the images taken in the laboratory was carried out (this process will be explained in detail later) (Bonaria, 2019).

3.4.1 MATLAB (programming language and numerical computing environment)

The MATLAB program was used to count the berries. The aim of using this software is to count the visible berries in the photos taken in the field and in the laboratory. MATLAB (short for Matrix Laboratory) is an environment for numerical calculation and statistical analysis written in C, which also includes the programming language of the same name created by MathWorks. MATLAB allows you to manipulate matrixes, display functions and data, implement algorithms, create user interfaces and interact with other programs. After creating a script specifically for the calculation of the yield estimate parameters, the images were loaded into MATLAB.

The counting took place manually with a simple click on each visible berry.

3.5 Image analysis

In this work, the image analysis will be divided into three separate data sets: manual laboratory images (1), manual field images (2) and VINBOT field images (3). Each dataset was collected under different conditions and included a total of 80 (1), 79 (2), and 90 (3) images, respectively. In all three datasets, the number of visible berries was performed using MATLAB (R2010b, the Mathworks, Natick, MA, USA).

Through a script, the program keeps track of the berries already counted and provides an Excel file (*Fig. 10*) with a sum of all the clicks made for each single image. The count was performed manually without the aid of an automatic algorithm, simply by clicking on each berry in the image, thus producing an estimate of the visible berries with the greatest possible accuracy. Then, these data, was used to estimate vine yield using the VINBOT platform. In the following sections, each dataset will be explained in detail.

3.6 Laboratory detailed measurements

On 2019 two pictures for cluster, one of the frontal side and one of perpendicular side with a blue background were taken. To maintain the same distance from the bunches, the camera was mounted on a tripod and moved, to take two pictures, between position reference present on the floor. The bunches were hung on a bar with the use of a metal spring where has been put a identification mark (example: AR_SP1_Meter2).

As we said in the chapter 3.4 total bunch weight was taken using a table scale (KERN FCB v1.4) and the berries were separated, photographed and then weighed without the rachis *(Fig. 9)*, in order to analyze berry weight, size and berry growth factor during the vine growing cycle.

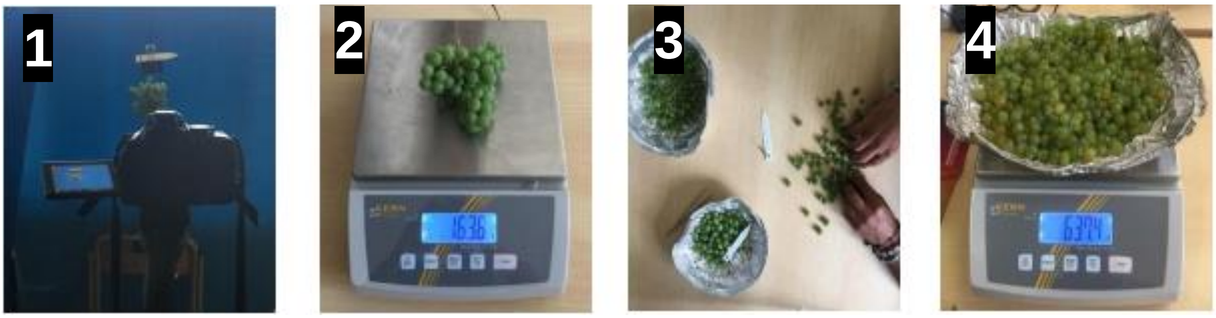


Figure 9 The detailed measurement performed in the laboratory on 2019, from the left to the right the blue background used to take the pictures of the bunches, the scale used to weight the bunches, the berries separation and the weight of the berries.

For first we counted the visible berries in 79 laboratory images. As said it the chapter image analysis, we analyzed the images through MATLAB with the aim of counting the total number of visible berries at bunch level (Vb_B) with a simply click on the berry *(Fig 10 A-C),* determining for each bunch, the Vb_B in the two different perspectives: “Vb_B side A”, which corresponds to the frontal prospective, and “Vb_B side B” which corresponds to the perpendicular prospective. Then we calculated the average Vb_B as the mean of visible berries from side A and side B, for each bunch. An average time of four minutes per photo was spent to count the berries under laboratory conditions

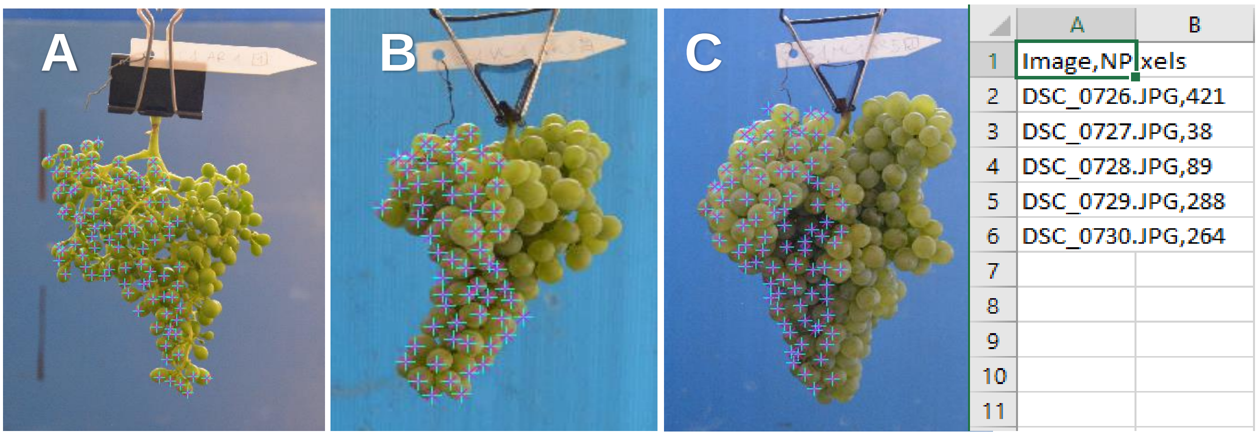


Figure 10 Example of MATLAB counting number of Arinto berries in the different phenological phases (A: pea-size, B: veraison, C: harvest) through the use of MATLAB.

That value was a useful tool to develop new models. We used the weight of the berries (g) obtained in the laboratory in 2019 for determining the average weight of the individual berry (g) (AbW) *(Eq.7):*

Equation 7

AbW (g)= Total berry weight (g) / Total berry number *(Eq.7)*

and then we have determined the average total weight of the berry and the berry growth factor (bGF) *(Eq.8)* on the all phenological stages:

Equation 8

bGF = AbW at maturation (g) / AbW at veraison (g) *(Eq.8)*

3.6.1 Estimation of berries occluded by other berries.

One of the main problems for the estimation of the yield by this method is the occlusion of berries by other berries, which depends on the degree of compactness of the bunch. In order to have an more accurate estimate of the yield the average number of occluded berries has been calculated.

To study this problem RGB images were taken in the laboratory during all phenological phases using a Nikon D5200 camera as previously described in paragraph “Detailed measurements”.

Once the number of berries for that cluster considering the two perspectives was determined, the average number of visible berries was calculated. This allowed us to obtain both the % of visible berries (*Eq.9*) and, consequently, the average percentage of occluded berries *(Eq. 10).*

The percentage of visible berries is the result of the *Eq.9*:

Equation 9 *(Eq.9)*

*% Vb_b = (Average Vb / Tb_L) * 100*

Using the result of equation 9 it is possible to obtain the average occluded berries (%) with the *Eq. 10*:

Equation 10 *(Eq.10)*

AbO_b (%) = 100 – (Average % Vb_L)

3.7 Estimation of berries covered by leaves

In 2019, 90 images were captured in the field (30 for both phenological phase) using a Nikon camera. From the images taken, different parameters were extracted: image area, background area and area of visible bunch. To have a homogeneous background and to facilitate the analysis, during the image acquisition, a blue panel was placed behind canopy.

The canopy porosity affects the bunch identification and consequently the berry detection, so the leaves can occlude the clusters and affect our detection ability, causing an estimation error.

The porosity of the foliage is calculated in %, the higher the porosity, the greater the % area of the visible clusters.

The sessions of image collection were set in two steps:

The first one was done to evaluate the canopy porosity and the occlusion of the bunches area at different levels of defoliation.

The second one was done to evaluate the percentage of berry by berry occlusion, the pictures were collected on three levels of defoliation:

- In *Figure 11* we see a blue background positioned behind the foliage to facilitate image analysis.on non-disturbed canopy vines *(Fig. 11A);*
- on vines with partially defoliated canopy at different levels *(Fig. 11B);*
- on vines with completely defoliated canopy *(Fig. 11C);*

Figure 11 Representation of the vines, at three different level of defoliation on fruit zone at the stage of maturation: without any defoliation (A), small defoliation (B), full defoliation (C).

For each level of defoliation (no defoliation, medium defoliation and total defoliation), the images were analyzed on MATLAB in the same way as in the laboratory.
The percentage of visible berries at the different level of the vine (Vb_v) was calculated using *Eq. 11:*

Equation 11

Vb_v (%) = (Vb_v at each defoliation level / Vb_v on totally defoliated vine) * 100 *(Eq.11)*

This technique was used to induce different levels of defoliation, in order to study the different visibility of the berries. The aim was to simulate different porosity realities and relate that trait to the percentage of visible berries, which should increase with a smaller amount of leaves.

Unlike laboratory conditions, the count of yield parameters in the field, using a camera, took about four to six minutes, as the occlusion caused by the leaves made it difficult to identify the clusters. *Figure 12* shows an example of berry counting with the MATLAB program in a completely defoliated canopy.

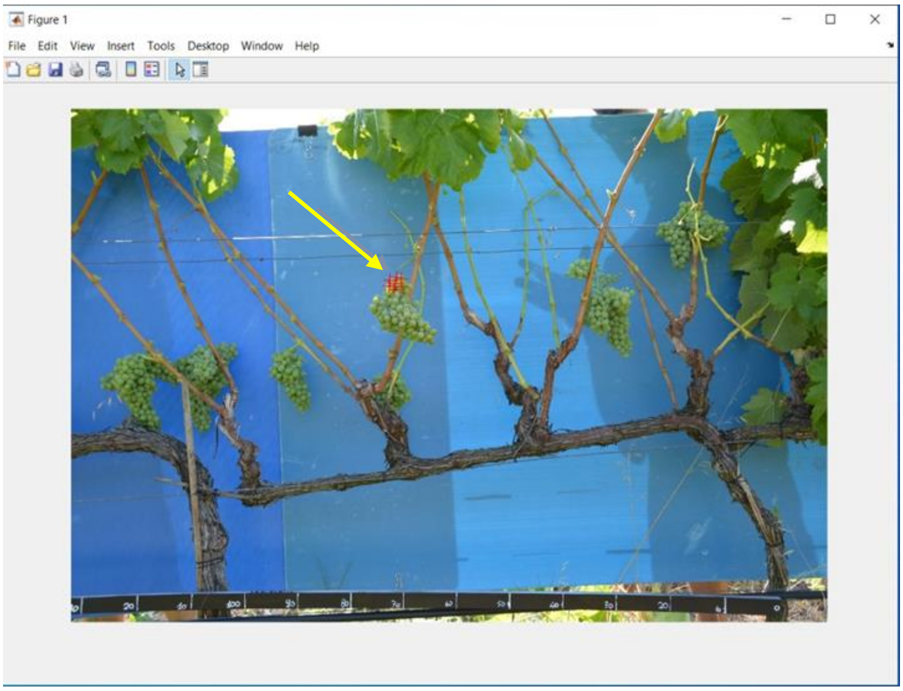


Figure 12 Analysis with MATlab. The yellow arrow indicates the clicks made with MATlab to determine the berries visible in a linear meter with canopy (image credit Gonçalo Victorino).

3.8 VINBOT detailed measurements

During the all phenological stages, 90 VINBOT images were obtained from all two SPs of the vineyard by passing the robot on one side of the row and maintaining a distance from the vines of 0,70 - 0, 80 meters.

To make image analysis easier and make the degree of porosity clearer a blue background has been placed behind the row. As the VINBOT automatic navigation system is still being developed, the platform was piloted using a wireless joystick system, and a smartphone was used to communicate, via Wi-Fi, with the platform and to manage the collection of images (Sama, 2019). At the end of maturation, all grape bunches were harvested from the analyzed vine segments and the final yield was obtained for each of the segment. On each acquired image *(Fig.13),* using image analysis,

Figure 13 Nikon photo in field condition, the leaves occlude the bunches increasing the time of detection and count of the bunches.

different attributes of the bunch and of the canopy were estimated, such as the projected area of the bunch in the image and the porosity of the canopy (Mauro, 2019).

Data that was used in this work for further evaluation. In the same images, the berries were manually counted, considering an LCM, as described in section 3.6.

Yield estimation was performed using a combination of two regression models developed with both field data (manual field images) and laboratory data (manual lab images).

The first model, obtained by a regression between % Porosity and % Visible berries (%Vb), estimates the proportion of visible berries that are being occluded by vegetation *(Eq. 12,13,14):*

Equation 12

$$\%Vb\_b = 22{,}296 * (\ln)\ Porosity + 3{,}5877\ \text{(pea-size)} \qquad \textit{(Eq.12)}$$

Equation 13

$$\%Vb\_b = 0.0251 * Porosity^2 + 3{,}1908\quad \text{(veraison)} \qquad \textit{(Eq.13)}$$

Equation 14

$$\%Vb\_b = 0{,}0266 * Porosity^2 + 3{,}307 \quad \text{(maturation)} \qquad \textit{(Eq.14)}$$

Using the measured the number of visible berries (Vbtot) we obtain the estimation of total number of berries that would be visible if all leaves were removed *(Eq.15)*

Equation 15

$$Vbtot = (Vb\_v / \%Vb\_b) * 100 \qquad \textit{(Eq.15)}$$

Yet this result does not give the total number of berries as many are still being occluded by neighboring berries. Therefore, a second model was used to estimate the total number of berries (btot) based on the btot from a 2D perspective *(Eq.16,17,18):*

Equation 16

$$btot = 2{,}6589 * Vbtot – 59{,}097 \quad \text{(pea-size)} \qquad \textit{(Eq.16)}$$

Equation 17

$$btot = 3{,}2592 * Vbtot – 60{,}465 \quad \text{(veraison)} \qquad \textit{(Eq.17)}$$

Equation 18

$$btot = 4{,}1313 * Vbtot – 129{,}49 \quad \text{(maturation)} \qquad \textit{(Eq.18)}$$

After applying both models the estimated yield (Est.Y) was obtained by multiplying the estimated total number of berries by the average berry weight (bW), obtained at harvest using the laboratory data *(Eq.19):*

Equation 19

$$Est.Y\ (kg) = btot * bW \qquad \textit{(Eq.19)}$$

This estimated yield was then compared with the actual yield and the percentage of error (% E) was determined with *Eq.20:*

Equation 20

$$\%\ E = ((Est.Y - Actual\ yield / Actual\ yield) * 100) \qquad \textit{(Eq.20)}$$

3.9 Data analysis

All data analysis was performed, from pea-size at maturation, using different statistical tests of analysis of data in Microsoft Excel. Correlation and regression analysis were performed to evaluate the relationships between variables. One-way ANOVA was conducted to compare the effect of the different bunch image perspectives (Vb_b side A and Vb_b side B).

4. RESULTS AND DISCUSSION

4.1Laboratory data

Tables 1 shows the average values for the different attributes of the bunch and berry determined in laboratory conditions and with image analysis, during the phenological phases of pea-size, veraison and maturation. The Arinto grapes shows an important increase in BW and bW values from pea-size to maturation, as does AbW. The increase of these values is given by the normal growth cycle of the berry.

Table 1 Summary statistics of variables measured and calculated on the Arinto grapes on pea-size, veraison and maturation. Variables studied: bunch weight (BW), berry weight (bW), average berry weight (AbW), total number of berry laboratory (Tb_L), visible berry in a bunch side A (Vb_B side A-B), average of visible berries in a bunch (Average Vb_B), % of visible berry laboratory (Vb_L), % average berry occlusion (AbO). Average ± Standard deviation .

PHENOLOGICAL STAGES	BW (g)	bW (g)	Tb_L	Vb_B side A	Vb_B side B	Average Vb_B	AbW (g)	Vb_L (%)	AbO (%)
PEA SIZE	57,5 ± 32,7	51,5 ± 30,1	233 ± 92,7	116 ± 36,43	103,7 ± 29,7	109,8 ± 31,9	0,21 ± 0.08	50,9 ± 12,4	40,1 ± 12,4
VERAISON	222,7 ± 127,5	210,5 ± 119,6	224,7 ± 130,4	83,3 ± 36,7	88,6 ± 39,5	87,5 ± 37,3	0,92 ± 0.2	43,5 ± 12,4	56.5 ± 23.4
MATURATION	405 ± 197,5	382,4 ± 186	297,8 ± 169	101,7 ± 37,2	105,2 ± 37,5	103,4 ± 36,5	1,37 ± 0,32	40,16 ± 11,9	58,8 ± 13.8

Tb_L has reached its maximum value in maturation, in fact if we look at the standard deviation this is very high. This means that although the averages are different, there is probably no statistical difference between the two values and that these differences are only because the clusters were slightly smaller but the number of berries is no different. The Vb_B side A-B and consequently the Average Vb_B, determined by the image analysis, reaches the maximum value in pea-size, this is because during this phenological phase, the grape has a smaller size and weight, decreasing the compactness of the bunch and consequently the berry occlusion. To confirm this theory is the value Vb_L (%) also in this case, the highest value is found in pea-size and consequently, we note how, always in pea-size, there is the lowest value of the percentage AbO (%).

4.1.1 Effect of bunch side on visible berry number

The variance analysis of the number of visible berry, between side A and side B, is carried out in all three phenological phases and the conclusions are different.

Carrying out the one way ANOVA test on veraison and maturation, we obtain 0.11 and 0.040 respectively, this means that between side A and side B there are no significant differences.

4.1.2 Correlation analysis for laboratory data

Table 2 shows the correlation coefficients (r) between the variables measured on the Arinto bunch, at pea-size, veraison and maturation. The regression analysis between BW and Average Vb_B presents a significative r the during the three phenological phases.

The high and significant correlation coefficients obtained indicate that these variables, if accurately detected, can be used as good explanatory for estimating the yield of the vine.

As for the number of berries, it is widely known that it explains a significant percentage of bunch weight (Clingeleffer, 2001). In fact, several authors used this variable as a predictor of grapevine yield (Diago et al., 2015; Grimm et al., 2018; Millan et al., 2018; Nuske et al., 2014; Zabawa et al., 2019). Results obtained in this work (Table 3) confirm that the number of berries can be used as a good predictor of bunch weight if all berries are visible.

With on-the-go yield estimation systems used in natural conditions, not all berries are visible and thus need to be estimated with the use of auxiliary variables or algorithms such as the Boolean model described in Millan et al. (2018).

Table 2 Pearson correlation coefficients between a selected set of variables for pooled data of Arinto grapes. The set of variables include: bunch weight (BW), total berries number (TB_l), average visible berries (Average VB_b).

Variables	PEA SIZE			VERAISON			MATURATION		
	BW (g)	**Tb_L**	**Average Vb_B**	**BW (g)**	**Tb_L**	**Average Vb_B**	**BW (g)**	**Tb_L**	**Average Vb_B**
BW (g)	1			1			1		
Tb_L	0,78***	1		0,93***	1		0,86***	1	
Average Vb_B	0,87***	0,92***	1	0,99***	0.93***	1	0.92***	0,89***	1

The * indicates the significance at P ≤ 0.5, ** indicates a significance at P ≤ 0.01, *** indicates a significance P ≤ 0.001. ns = not significant

4.1.3 Laboratory models to estimate the relationship between the total berry number and average number of visible berries

The linear regression model developed at pea-size, veraison and maturation shows the relationship between the average number of visible berries (independent variable) and the total berry number (dependent variable). This relationship has a good coefficient of determination but different for the three phenological phase. These value of R^2 was 0,83 at pea-size (*Fig.14A*), 0,86 at veraison (F*ig. 14B*) and 0,79 at maturation (*Fig. 14C*). Based on the R^2 we can confirm that the regressors predict well the value of the dependent variable in the sample.

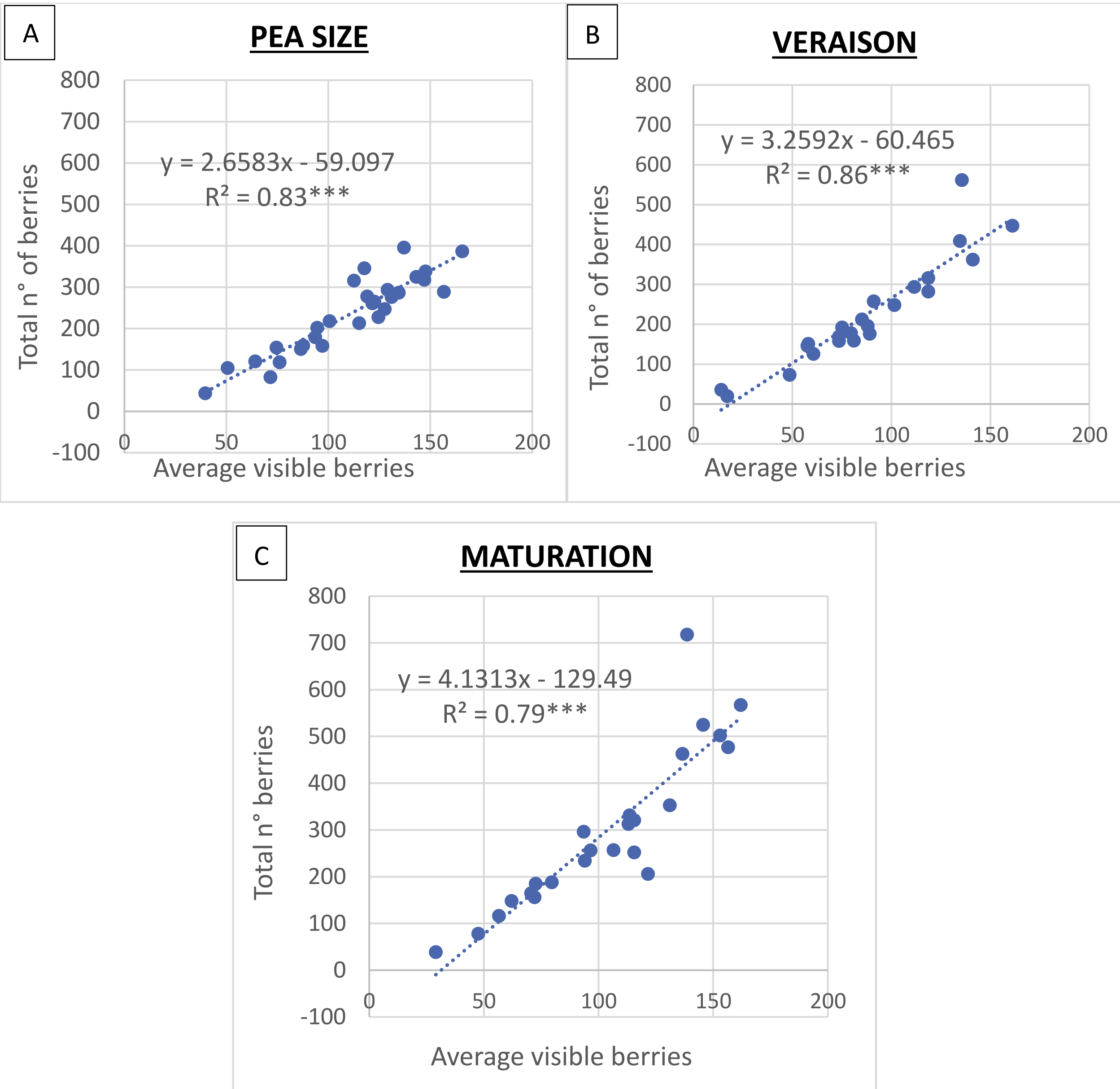


*Figure 14 Relationship between Total number of berries (dependent variable) and Average visible berries (independent variable) with respective linear regression equations and coefficient of determination (R^2) at pea-size (A), veraison (B), and at maturation (C). The *** indicates the significant R^2 at p≤0.001.*

4.1.4 Relationship between the average number of visible berries and bunch weight

These linear regression models shown the relationship between the number of visible grapes (independent variable) and the total weight of the bunches (dependent variable). The best value was in veraison R^2= 0.93 (*Fig.15 B*). The regression presented a significant R^2 in the all phenological phase. Consequently we can say that the regressors predict well the value of the dependent variable in the sample. We can confirm that the number of visible berries explains a very high percentage of bunch weight variability.

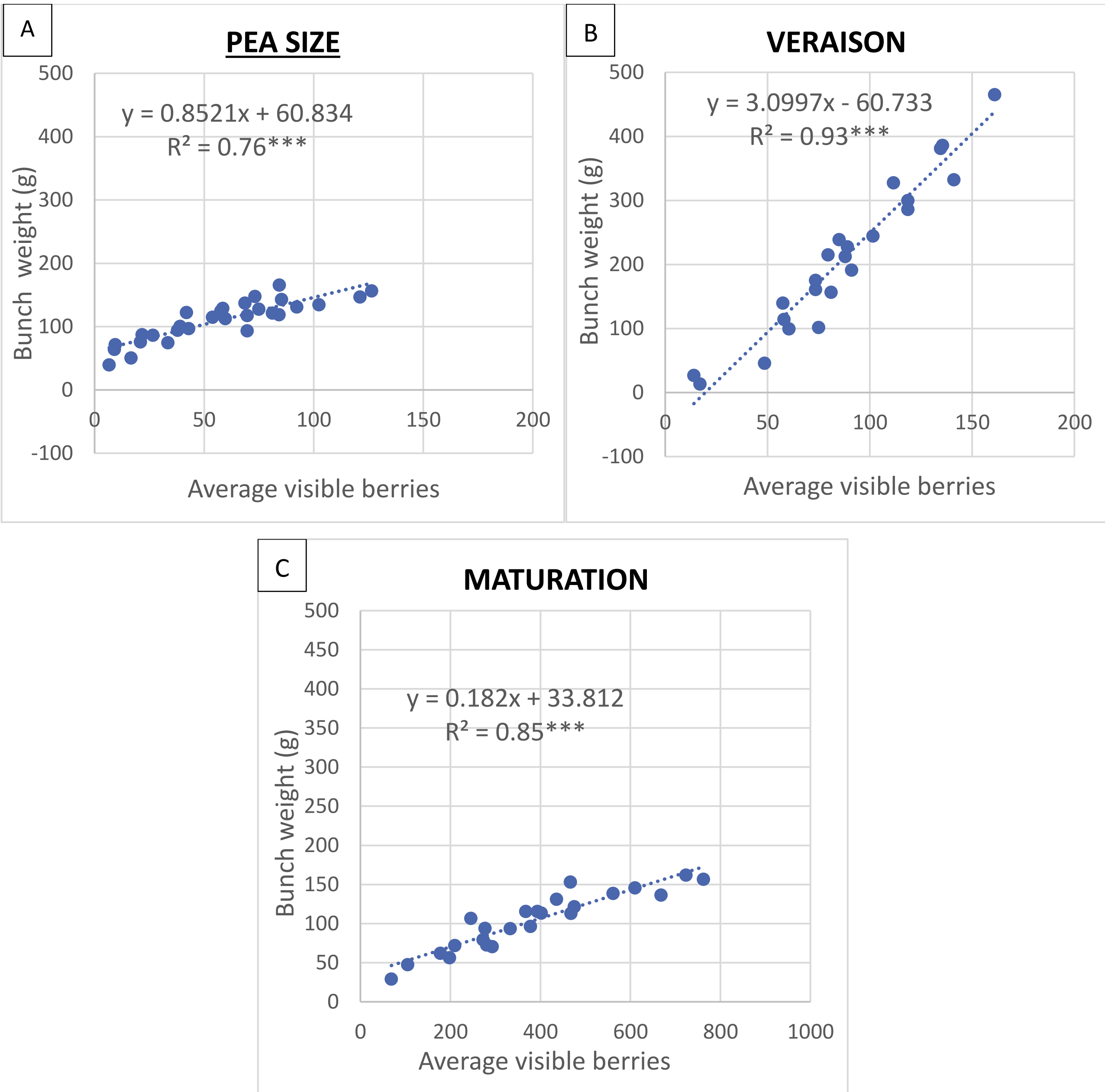


*Figure 15 Relationship between Average visible berries (independent variable) and Bunch weight (g) (dependent variable) with respective linear regression equations and coefficient of determination (R^2) at veraison (A) and at maturation (B). The *** indicates the significant R^2 at p≤0.001.*

4.2 Field manual images

Table 3 presents the average values, in field conditions, for the canopy porosity (P%), VBA and % (estimated manually using the ImageJ software) of Vb_v, (estimated manually using the MATLAB software) on vines with different levels of defoliation (no defoliation, medium defoliation, total defoliation).

The mean VBA and % of Vb_v increase proportionally with the increase in the level of defoliation, as berries can be more easily conceived. This because we are gradually removing more leaves creating more empty spaces in the canopy and, consequently, exposing the bunches more, decreasing the occlusion (Table 3). This increase in canopy porosity is explained by the fact that as the level of defoliation increases, we are gradually removing more leaves creating more empty spaces in the canopy and, consequently, exposing the bunches more. These results confirm the thesis that if the porosity increases, the number of visible berries also increases (Lopes et al., 2017).

Table 3 Average values (± standard deviation) of the % porosity (P (%)), the visible bunch area (VBA) and the % of visible berries at vine level (Vb_v) on Arinto vines with different degrees of defoliation during the phenological stages: pea-size, veraison and maturation.

Defoliation degree	*PEA SIZE*			*VERAISON*			*MATURATION*		
	P (%)	**VBA (cm^2)**	**Vb_v (%)**	**P (%)**	**VBA (cm^2)**	**Vb_v (%)**	**P (%)**	**VBA (cm^2)**	**Vb_v (%)**
No	2,4 ± 1,4	92 ± 0,14	18,8 ± 15	5,13 ± 2,5	108,5 ± 96,8	27,9 ± 15,3	7,4 ± 5,2	190 ± 119	25,8 ± 13,5
Partial	6,3 ± 2,7	228 ± 0,22	40,8 ± 20,8	16,1 ± 8,9	303,5 ± 267,1	42,1 ± 19,9	13,5 ± 7	342 ± 216	44,7 ± 19,8
Total	68,3 ± 3,3	417 ± 163	100	71,1 ± 4,57	644 ± 339	100	67,7 ± 7,7	817 ± 334	100

4.2.1 Correlation analysis

Table 4 shows the correlation coefficients (r) between the variables of the field manual images, at pea-size, veraison and maturation. P% presented high and significant r values with Vb_v in the all phenological phases. The actual yield (Y) doesn't show an significative and positive r in every correlation, for example on pea-size the correlation between Y and Vb_v is significant and positive. These variables with positive and high r, if detected in the appropriate way, are excellent explanatory variables for estimating the yield in the vineyard.

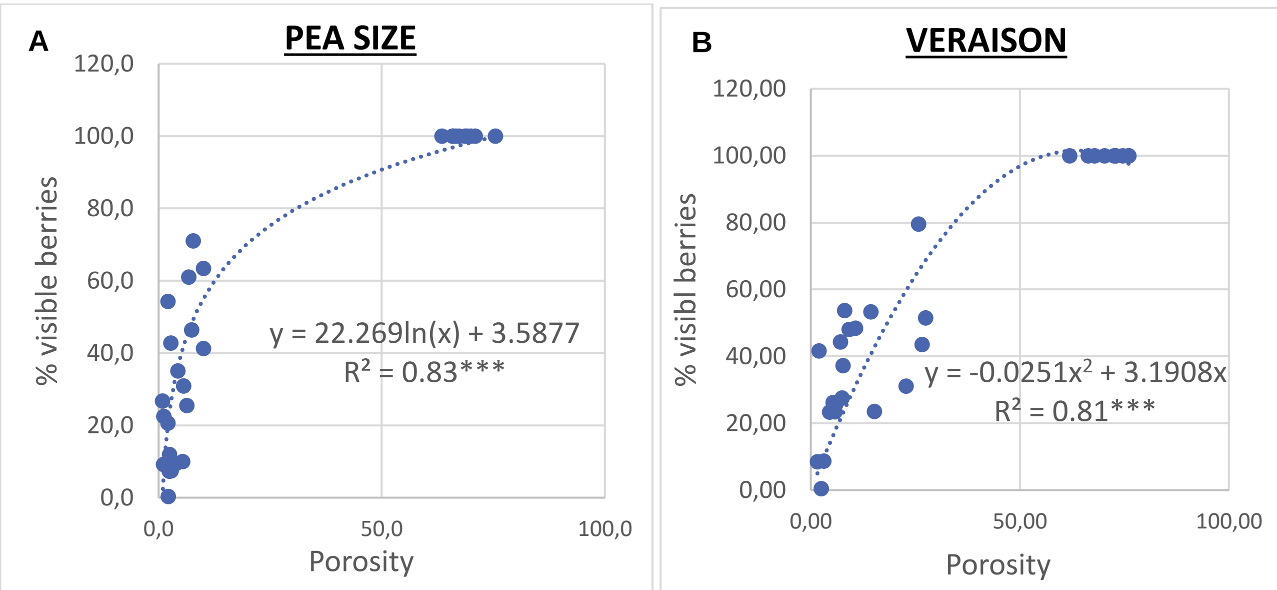
Table 4 Pearson correlation coefficients between a selected set of variables for pooled data under field conditions. The set of variables include: visible berries (Vb_v), % porosity (P (%)), visible bunch area (VBA) and actual yield (Y).

Variables	*PEA SIZE*				*VERAISON*				*MATURATION*			
	Vb_v	**P (%)**	**VBA**	**Y**	**Vb_v**	**P (%)**	**VBA**	**Y**	**Vb_v**	**P (%)**	**VBA**	**Y**
Vb_v	1				1				1			
P(%)	0,76 ***	1			0,61 ***	1			0,71 ***	1		
VBA	0,47 ***	0,68 ***	1		0,71 ***	0,65 ***	1		-0,29 ns	0,68 ***	1	
Y	0,42 ***	0,00 ns	0,47 ***	1	0,08 ns	-0,03 Ns	0,07	1	-0,22 ns	0,07 ***	0,29 ***	1

The * indicates the significance at P ≤ 0.5, ** indicates a significance at P ≤ 0.01, *** indicates a significance P ≤ 0.001. ns = not significant

4.2.2 Models to estimate the berries covered by leaves

Figure 20 A-C shows the regression model between the% porosity (P (%)) (independent variable) and the% visible berries not covered by leaves (Vb_v) (dependent variable). This estimate shows the same R^2 between pea size (*Fig. 16A*) and maturation (*Fig.16C*), 0.81 at Veraison (*Fig. 16B)*, in all cases R^2 has excellent significance, therefore, it is possible to use this model to estimate the berries covered by the leaves.



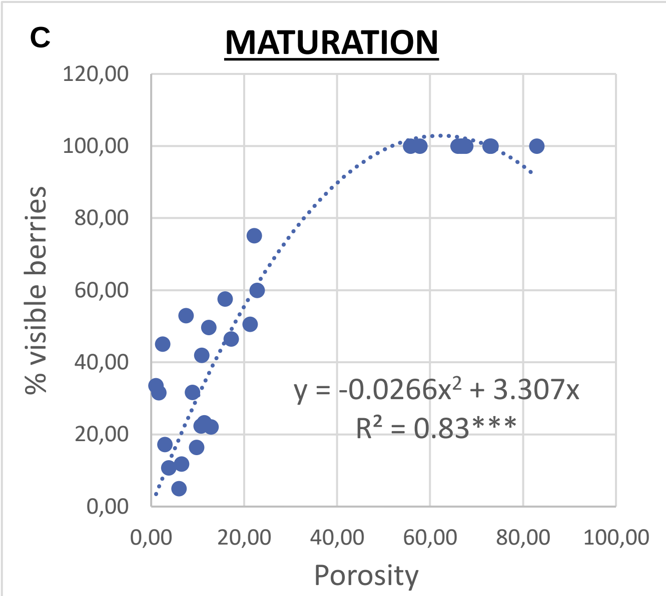
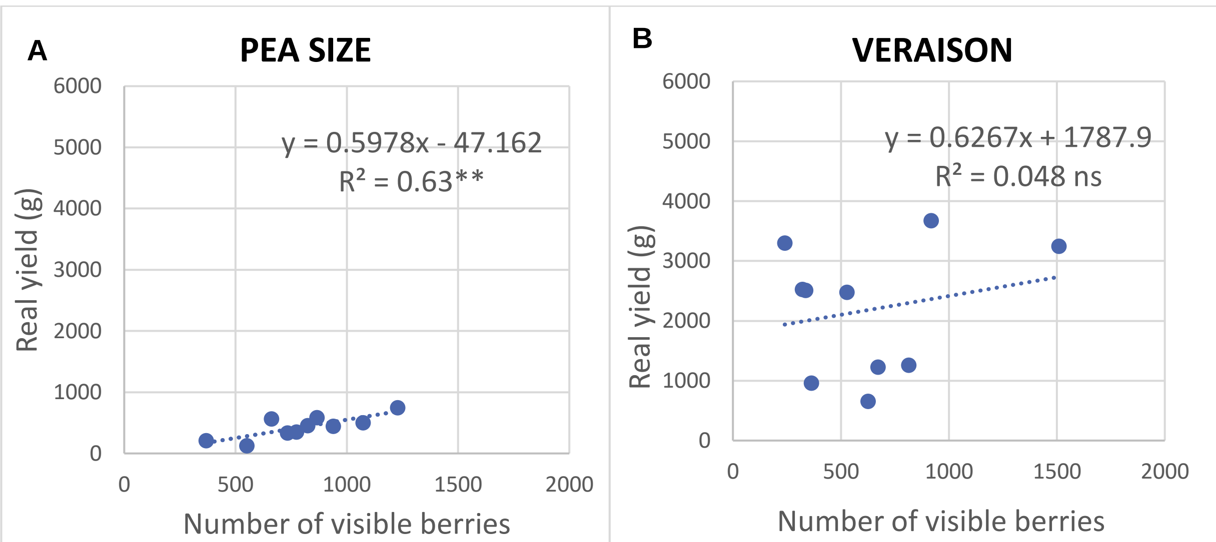


*Figure 16 Relationship between the porosity (P) and the % of visible berries (Vb_v) not covered by leaves with respective polynomial regression equations and coefficient of determination (R2) at pea-size (A), veraison (B) and at maturation (C). The *** indicates the significant R^2 at p≤0.001.*

4.2.3 Relationship between the visible berry number and the actual yield

In pea size we find a higher R^2 due to the lower "berry by berry" occlusion. Results in veraison an maturation confirm this theory, infact in pea-size we found the largest number of visible berries associated to the lowest yield estimate; in veraison the yield value was greater than the one in pea-size but lower than the one found in maturation, with a number of visible berries lower than the pea size and greater than maturation. Finally, during maturation the yield estimation was higher but the count of visible berries lower, may be caused by the increase in the size of the berries that cause greater "berry by berry" occlusion.



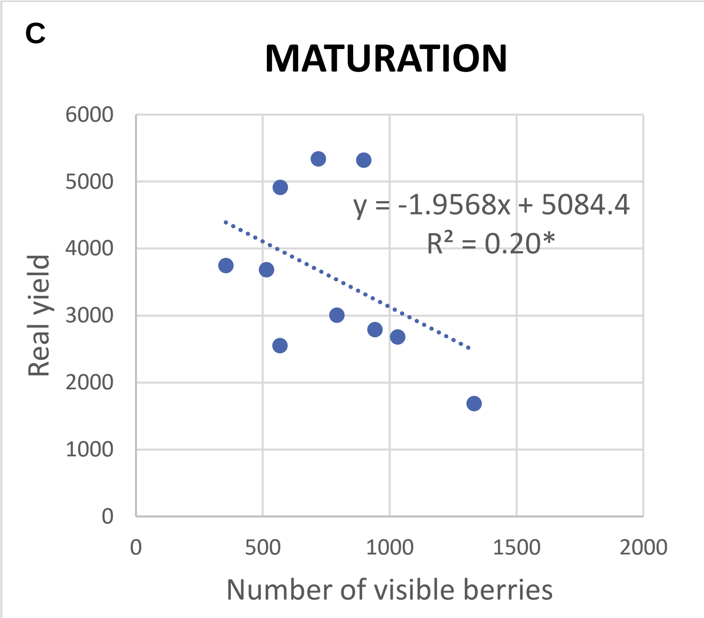


*Figure 17 Relationship between the visible berries (independent variable) Real yield (g) (dependent variable) with respective linear regression equations and coefficient of determination (R^2) at maturation (A). The *** indicates the significant R^2 at p≤0.01 and *** indicates the significant R^2 at p≤0.001. The ns indicates that there is no significance.*

4.3 Yield estimation with VINBOT

Table 5 shows the average values of different variables obtained in field conditions using the images captured with the VINBOT platform, during the phenological phase pea-size, veraison and maturation. In VINBOT more berries were identified at pea size than veraison and maturation.

This demonstrates that the high VBA makes them more easily differentiated from vegetation (Table 5). According to Gonçalo et al. (2020), on a fully developed canopy and without defoliation, the average visible area of the bunch increases from pea size to maturation, probably because the area of the bunch has increased. This can also be stated in laboratory conditions (Table 1), which showed increases in the BW, stating an increase in the VBA in field conditions. The highest number of counted berries has probably been found at pea-size due to the smaller size of the undeveloped berries which decrease the berry by berry occlusion.

Vbtot is directly proportional to Vb_v at pea-size and veraison but not at maturation, consequently we have an Vbtot, excluding the occlusion of the leaves, greater at pea size, given the fact that in this phenological phase Vb_v was greater than at veraison and maturation.

The btot is directly proportional to Vb_v, as one increases the other increases, in this case we have estimated a btot, excluding both the occlusion of the leaves and berries, greater at pea-size, again to have a Vb_v greater than at veraison and maturation. Having estimated a higher btot during pea-size, consequently the Est.Y, in this phase, is also higher.

Table 5 Summary statistics of measured and calculated variables in field conditions using the VINBOT platform and image analysis in pea-size, veraison and maturation: number visible berries (Vb_v), % of porosity (P), visible bunch area (VBA), % of visible berries (%Vb_b), visible berries excluding occlusion from leaves (Vbtot), visible berries excluding occlusion from leaves and berries (btot), yield estimate (Est.Y). Average ± standard deviation; Max: maximum value; Min: minimum value.

	PEA SIZE			VERAISON			MATURATION		
	Min	**Avg**	**Max**	**Min**	**Avg**	**Max**	**Min**	**Avg**	**Max**
Vb_v	0	111,3±84,1	337	0	71,7 ± 57,3	239	0	70 ± 60.6	253
P (%)	1	4,1±2,7	12	1	4,2 ± 2,9	11,5	0.9	5 ± 3,6	14,7
VBA (cm^2)	0	109±89,7	283	0	106,3 ± 74	256,9	0	163,9 ± 129	509,2
% Vb_b	3,6	30,2±16,2	58,9	3,1	12,6 ± 8,4	33,4	3	15,4± 10.5	42,9
Vbtot	0	641±968,3	3985	0	798,4 ± 848	3076	0	559± 532	2100
Btot	59	1647±2547	10536	60,5	2541±2764	9967	0	2193± 2185	8547
Est.Y (kg/m)	0,1	2,3±3,5	14,5	0,1	3,5± 3,8	13,7	0	3 ± 3	11,8

Table 6 shows the Est.Y using VINBOT compared with the Actual yield and the determination of the % of Error which, in our case, the results are very good in the all phenological phases, especially on maturation.

Table 6 Determination of yield in field conditions by using VINBOT at veraison and at maturation: estimated yield (Est.Y), actual yield (Y), % error (E).

Phenological phase	**Est.Y (Kg/40meter)**	**Y (kg/40meter)**	**E (%)**
Pea size	45,3	54,9	-18%
Veraison	69,9	54,9	27%
Maturation	60,3	54,9	10%

CONCLUSIONS

Through this thesis work we wanted to use the number of berries visible on the images of the bunch and of the canopy to estimate the yield at three phenological phases (pea-size, veraison and ripening) in an experimental vineyard with the white variety Arinto. From the data obtained in the laboratory through the analysis of images, it was found that there is a high correlation between the number of visible berries and the weight of the bunches, reaching the conclusion that the number of visible berries can be considered a good explanatory variable of the weight of the bunch especially when ripe. The regression analysis between the porosity of the canopy and the number of berries visible in the images highlighted high and significant coefficients of determination, which were very similar between the phenological phases studied. With the regression analysis between visible berries and actual yield, the most significant R^2 was obtained at maturation, so we can say that the number of visible berries is a good explanatory variable of the actual yield, in particular when ripe. Finally, the yield of the vineyard at veraison and ripening was estimated using the images captured by the VINBOT platform and was compared with the actual yield. We obtained an underestimation at pea-size, and an overestimation at the other stages being the highest error at veraison and the lower one at maturation ripening. Based on the results obtained in this work, we can conclude by saying that image analysis can be an alternative to traditional and manual methods to estimate vineyard yield, but further research is still needed in order to improve the algorithms accuracy.

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