Assessing berry number for grapevine yield estimation by image analysis: case study with the white variety "Encruzado"

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ABSTRACT

Nowadays, yield estimation represents one of the most important topics in viticulture. It can lead to a better vineyard management and to a better organization of harvesting operations in the vineyard and in the cellar. In recent years, image analysis has become an important tool to improve yield forecast, with the advantages of saving time and being non-invasive. This research aims to estimate the yield of the white cultivar 'Encruzado' using visible berry number counted in the images aquired at veraison and near harvest, using a manual RGB camera and the robot VINBOT. Images were collected in laboratory and in the field at the experimental vineyard of the Instituto Superior de Agronomia (ISA) in Lisbon. In the field images the number of visible berries per canopy meter was higher at maturation than at veraison, respectively 72.6 and 66.3. Regarding the percentage of visible berries, 30.2% where visible at veraison and 24.1% at maturation. Concerning percentage of berries occluded by other berries it was observed 28.7% at veraison and 24.3% at maturation. Regression analysis showed that the number of berries in the image explained a very high proportion of bunch weight variability, R^2=0.64 at veraison and 0.91 at maturation. Regression analysis also showed that the canopy porosity explained a very high proportion of visible berries variability, R^2=0.81 at veraison and 0.88 at maturation. The obtained regression models underestimated the yield with an higher error at veraison than at maturation. This underestimation indicates that the use of visible berry number on the images to estimate yield still needs further research to improve the algorithms accuracy.

Key worlds: Algorithm, Image Analysis, Precision Viticulture, Robotics, Yield Estimation.

RESUMO

Hoje em dia, a estimativa de rendimento representa um dos tópicos mais importantes da viticultura. Pode levar a uma melhor gestão da vinha e a uma melhor organização das operações de colheita na vinha e na adega. Nos últimos anos, a análise de imagem tornou-se uma ferramenta importante para melhorar a previsão de produtividade, com as vantagens de economizar tempo e não ser invasiva. Esta pesquisa tem como objetivo estimar o rendimento da cultivar branca 'Encruzado' utilizando o número de bagos visíveis contados nas imagens adquiridas na época do pintor e próximo à colheita, utilizando uma câmera RGB manual e o robô VINBOT. As imagens foram recolhidas em laboratório e em campo na vinha experimental do Instituto Superior de Agronomia (ISA), em Lisboa. Nas imagens de campo, o número de bagos visíveis por metro de sebe foi maior na maturação do que no pintor, respectivamente 72.6 e 66.3. Em relação à percentagem de bagos visíveis, 30.2% estavam visíveis na época do pintor e 24.1% na maturação. Quanto à percentagem de bagos encobertos por outros bagos, foi observada 28.7% na fase de pintor e 24.3% na maturação. A análise de regressão mostrou que o número de bagos na imagem explica uma proporção elevada da variabilidade do peso do cacho, R^2=0.64 na época do pintor e 0.91 na maturação. A análise de regressão também mostrou que a porosidade da sebe na zona de frutificaçaõ explica uma proporção elevada da variabilidade do número de bagos visíveis, R^2=0.81 no pintor e 0.88 na maturação. Os modelos de regressão obtidos subestimaram o rendimento com maior erro no pintor que na maturação. Essa subestimação indica que o uso do número de bagos visíveis nas imagens para estimar o rendimento ainda precisa de mais investigação de forma a melhorar a precisão dos algoritmos.

Palavras-chave: Algoritmo, Análise de Imagens, Viticultura de Precisão, Robótica, Estimativa de Rendimento.

RESUMO ALARGADO

Hoje em dia, a estimativa de rendimento representa um dos tópicos mais importantes da viticultura. Na verdade, pode levar, em primeiro lugar, a uma melhor gestão da vinha, aplicando as práticas culturais adequadas no tempo, com o objetivo de produzir vinhos de alta qualidadee, em segundo lugar, a uma melhor organização das operações de colheita na vinha e na adega. No passado, os métodos manuais têm sido utilizados para a recolha de dados para a previsão da produtividade da vinha, no entanto, nos últimos anos, de forma a melhorar a previsão, a análise de imagempassou a ser uma ferramenta com grandes potencialidades pois é mais económica, não invasiva e poupa tempo. Esta investigação visa determinar a eficácia da contagem do número de bagos na imagem para estimar a produtividade durante o período de pintor e maturação, através da análise das imagens colhidas em laboratório e pelo robô VINBOT na vinha. Esta investigação foi realizada na vinha do Instituto Superior de Agronomia em Lisboa durante a época de 2019 utilizando a casta branca 'Encruzado'. As imagens no vinhedo foram adquiridas quer com uma câmera RGB manual, quer com uma câmera RGB-D posicionada no Vinbot, enquanto no laboratório apenas se utilizou a câmera RGB manual. Durante as fases fenológicas analisadas, foi avaliada a correlação entre o que é visto com o Vinbot e o que é visto nas imagens. Dos resultados obtidos em laboratório, foram consideradas duas relações, a primeira entre a média dos bagos visíveis e o número total de bagos, a segunda entre a média dos bagos visíveis e o peso do cacho. No laboratório verifica-se, desde o pintor até à maturação, um aumento do peso dos bagos de 1.4 para 2 g e uma diminuição do número médio de bagos visíveis na imagem 60 para 46.1. Quanto à percentagem de bagos encobertos por outros bagos, foi observada 28.7% na fase de pintor e 24.3% na maturação. Analisando as imagens captadas em campo, foi determinada a visibilidade dos bagos com diferentes níveis de desfolha e a análise das relações rendimento real/bagos visíveis e porosidade/% bagos visíveis, que apresentaram ambas um elevado coeficiente de determinação. Verificou-se também que o número de bagos visíveis no campo por segmento de sebe avaliadofoi maior na maturação do que no pintor, respectivamente 72.6 e 66.3. Quanto à fracção de bagos visíveis verificou-se um valor de 30.2% ao pintor e 24.1% na maturação. A análise de regressão mostrou que o número de bagos na imagem explicava uma proporção elevadada variabilidade do peso do cacho, R^2=0.64 na época do pintor e 0.91 na maturação. A análise de regressão também mostrou que a porosidade da sebe na zona de frutificação explicava uma proporção elevada da variabilidade da fracção de bagos visíveis (R^2=0.81 no pintor e 0.88 na maturação). Por fim, o rendimento estimado foi comparado com o rendimento real, obtendo-se um erro de -56.7% no pintor e -18.3% na maturação. Os erros ainda são elevados em ambas as estimativas, em particular na época do pintor, pois, em determinados momentos do ciclo vegetativo, este método não permite visualizar um elevado número de bagos devido à oclusão de bagos por outros bagos. Em suma pode-se afirmar que o uso do número de bagos visíveis nas imagens como variável explanatória do rendimento pode ser uma alternativa aos métodos tradicionais, mas precisa ainda de ser melhorada quer no que diz respeito à qualidade das imagens do robô quer relativamente ao problema relacionado com a oclusão de bagos por outros bagos e por outros órgãos vegetativos.

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2D = Two- dimensional

3D = Three-dimensional

a* = Greenness-redness coordinate

AbO_b = Average berry occlusion by other berry

ABV = Actual bunch volume

AbW = Average berry weight

b* = Blueness-yellowness coordinate

btot = Total number of berries

bW = Berries weight

BW = Bunch weight

CIE = Commission International d'Eclairage

CIELAB = Color space CIE L*a*b

E = Error between actual and estimated yield

GBCNet = Grape Berries Counting Net

GIS = Geographic Information System

GPS = Global Positioning System

HMI = Human machine interface

HSB = Hue, Saturation, Brightness

IF = Fruitfulness Index

IPMA = Instituto Português do Mar e da Atmosfera.

ISA = Instituto Superior de Agronomia

L* = Luminance coordinate

LAI = Leaf Area Index

LCM = Linear Canopy Meters

LiDAR = Light Detection and Ranging

NDVI = Normalized Difference Vegetation Index

NIR = Near Infrared

OIV = International Organization of Vine and Wine

P = Porosity

PQA = Point Quadrat Analysis

PV = Precision Viticulture

RGB = Red, Green, Blue

ROI = Region of Interest

Rtot = Accumulated rainfall

SMPH = Semi Minimal Pruned Hedge

SP = Smart point

$\mathbf{T_{t,\,a}}$ = Trellis wire tension at the time “t” from the previous year

$\mathbf{T_{t,\,c}}$ = Trellis wire tension at time “t” of the season

Tb_L = Total number of berry “laboratory”

TTM = Trellis Tension Method

Tmed = Average temperature

UAV = Unmanned aerial vehicles

VBA = Visible bunch area

Vb_B = Visible berries at bunch level

Vb_L = Visible berries “laboratory”

Vbtot = Visible berries with removal of all leaves

Vb_v = Visible berries at vine level

VSP = Vertical Shoot Position

Y = Actual yield

Y_a = Yield from the previous year

Yest = Estimated yield

% Vb = % Visible berries

$Y_{t,\ c}$ = Forecast of the yield at any time "t" of the season

1. INTRODUCTION

The cultivation of grapes is widespread in all parts of the world whereas climatic conditions allow it.

Monitoring the health and maturation status of the grapes during the cultivation cycle is fundamental for high quality production (Bindon et al., 2014; Ivorra et al., 2015; Portales and Ribes-Gomez, 2015; Pothen and Nuske, 2016), but the yield monitoring in terms of the number and size of bunches is important as well (Fanizza et al., 2005; Cabezas et al., 2006; Costantini et al., 2008). Nowadays, these procedures are made easier by the introduction of sensors and other technologies in viticulture.

In viticulture there are several automated cultural practices while others are in a development phase. In recent decades, robots have been introduced into the field, these are mobile platforms that allow to collect and map a lot of data on crops, such as canopy temperature, vigor, yield, grape composition, by deploying sensors (Lopes et al., 2017).

An accurate forecasting of the yield for the winery is important for several aspects.

Such a forecasting can help the winegrower to manage the vineyard and to organize the cellar, thus increasing the efficiency of operations (Cunha et al., 2010). For example, it helps to select some cultural practices if it is necessary (bunch thinning, fertilization planning), to organize the harvest (defining labour and machinery needed), to plan cellar needs (availability of the space in tanks or barrels for the winemaking, oenological products, bottles) to establish grape price, to manage wine stocks, grape and wine market, to program investments and to develop marketing strategies (Dunn and Martin, 2004). The yield in the vineyard can be influenced by several biotic and abiotic factors, which have an affect on the number and size of berries, therefore it is essential to understand the most suitable phenological phase to perform an estimate of yield as accurate as possible. The methods for yield estimation can be applied during the whole growing cycle. If the yield forecast is anticipated there is a greater risk of inaccuracy, whilst if it is carried out close to the harvest, the accuracy of the yield is higher, but nonetheless there is no time to apply the cultural practices in vineyard to improve the quality of the grapes. The veraison is the most commonly used phenological phase to estimate the yield because it allows winegrowers and winemakers to promptly apply their plans if necessary, for example the bunch thinning in order to avoid an excessive yield production which might lower its quality, furthermore such a phase avoids to comprimise the yield accuracy being it close to the harvest phase (Dunn and Martin, 2004).

Several methods can be applied to estimate the yield. In general many of them are based on the estimate of the yield components (Clingellefer et al., 2001), such as the number of the bunches, berries per bunch and the berry weight (Tardaguila et al., 2012; Nuske et al., 2014). These manual methods have several disadvantages: they are highly destructive and require intense labour which implies a lot of time with inaccurate results given by samples that are not representative of the vineyard (Pothen and Nuske, 2016). In fact the variability of the yield in the vineyard has been proven to be high (Bramley and Hamilton, 2004). Furthermore, the manual forecast of the yield is highly influenced by the subjective evaluation of each operator, thus compromising the accuracy of the estimate (Roscher et al., 2014).

In the last decades many experiments have been developed with the aim of applying image analysis technologies for bunches and/or berries as to avoid human error, to reduce labour costs and to achieve more accurate yield prediction.

Recently, a mobile robot (VINBOT) has been developed in the frame of EU reseach project with the ability to acquire and analyze RGB images and data through a set of sensors, in order to know the variability in the vineyard in terms of yield.

The first experiments were conducted in experimental vineyards in Lisbon with positive results as regards the vegetative aspects, such as the exposed leaf area. On the contrary the results relating to the yield estimate were less accurate (error of 15.2 %) mainly due to the occlusion of the bunches (Lopes et al., 2017).

Further research will be needed to improve the results of this robot.

Many of these researches use different algorithms to determine the yield, all reaching positive results. However, such a positive attainment depends on the visibility of the bunches which are in turn influenced by the density of the canopy in the fruiting zone and by the number of bunches (Victorino et al., 2019).

2. AIMS OF THE WORK

In this research we are using images obtained previously by ISA research team in the frame of the VINBOT (www.vinbot.eu) project because of the COVID-19 pandemic.

The aims of the present work are:

- To improve crop forecasting through the study of an economical, non-destructive and time-saving yield estimation technique;
- To develop models usefull firstly to estimate the non visible berries during veraison and full ripeness, and secondly to obtain the yield estimation;
- To estimate yield at veraison and close to harvest and to compare it with the real yield obtained at harvest.

3. LITERATURE REVIEW

3.1 Precision viticulture

At a time of continuous growth of competition in international wine markets, it is necessary to achieve higher quality standards in the vineyard. This implies the use of precision viticulture (PV) which manages the vineyard system in an increasingly efficient way by making use of new technologies, supporting growers decisions, maximizing the crop quality, without neglecting environmental sustainability. We can decrease production costs while safeguarding the environment through the reduction of external inputs such as energy, fertilizers and chemicals (Fernandez et al., 2013; Matese and Di Gennaro, 2015).

The precision viticulture is a technique developed in the mid-80s with the concept of managing and monitoring of spatial variation in any physical, biological and chemical variables that means management differentiation of each parcel of the vineyard in order to fulfil the real needs (Hall, 2002; Matese and Di Gennaro, 2015). Indeed there is a high variability both between the vines and within the vine itself, with direct consequences on the yield and the grapes quality (Matese and Di Gennaro, 2015). Variability in the vineyard can be due to several factors, for example soil characteristics such as: structure, texture, depth, water and nutritional availability, exposure or weather conditions, plant health, cultivation practices (Boselli et al., 2016). Thanks to precision viticulture it is possible to study the characteristics of the soil, water availability, vigor of plants, attacks on plants by pathogens, composition and yield of fruits. This is possible thanks to data obtained from technologies such as Global Positioning System (GPS), Geographic Information System (GIS) which are the basis of precision viticulture (Matese and Di Gennaro, 2015; Searcy, 2008).

3.2 Vineyard monitoring technologies

Through monitoring processes, an attempt is made to acquire the maximum amount of data relating to the vineyard. Several tools, platforms and sensors have been designed to monitor different vine parameters, which serve to increase precision-focused viticulture.

Some of these instruments are focused on reflectance spectroscopy, measuring the reflectance of the electromagnetic radiation incident at different wavelengths, such as the visible region (400-700 nm), the near infrared (700-1300 nm) and the thermal region (7500-15000 nm).

Moreover for the detection of vigor, nutritional status or plant health, it is possible to use a multispectral or hyperspectral sensor of which we will discuss later.

The sensors can be either portable tools or mounted on fixed platforms and positioned on the area of interest. Among the most popular platforms there are robots, drones, planes,

helicopters and satellites, all of which have advantages and disadvantages that can be related to the costs, the availability and resolution of the images (Jones e Vaughan, 2010).
Many of the platforms are based on satellite navigation systems such as the GPS and other types of sensors, which have favoured the management of variability in the vineyard.
Precision agriculture is based on several systems like the GPS system and GIS. The former is fundamental for the accuracy of the coordinates because of the identification of the position of a point on the earth's surface (Searcy, 1997), the latter is equipped with a database that analyzes and manages the spatial rapresentation as to have a perception of space and evaluate data (Hall et al., 2002).
Based on the distance of application, we can divide the monitoring technologies into two groups: Remote sensing and Proximal sensing. While the first one includes aerial imaging, the second one uses sensors in close range to the analyzed object.

3.2.1 Remote sensing

Remote sensing allows the acquisition of data/images from a distance by detecting and recording the electromagnetic radiation reflected from the surface of objects on the ground (Hall et al., 2002). The application of remote sensing in agriculture provides information on different traits of the vine, such as shape, size and vigour and enables the user to evaluate the variability within the vineyard.
The calculation of vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), based on collected data, allows the computing of vigor maps to monitor the vegetative state of the plants.
The NDVI index is calculated by using the following equation (Eq. 1):

Eq. 1 $NDVI = (NIR – RED)/ (NIR + RED)$

Where Near Infrared (NIR) represents the reflection in the near infrared wavelength band while RED represents the reflection in the red band. NDVI values are between 0 and 1 and are related to the state of vegetation health (Gitelson et al. 2004, Hall et al. 2002).

Three different platforms are used in remote sensing: satellites, aircrafts and unmanned aerial vehicles (UAV). In precision viticulture the use of the satellite is not sufficient due to some limitations such as the reduced space resolution (number and size of pixels), the temporal resolution (number of images per period of time) and the possibility of cloud cover that can occur during the passage of the satellite. The use of aircraft avoids some limitations,

for example, it schedules the time acquisition of images and provides a higher image resolution, depending on the flight altitude.
They can fly under cloud cover and avoid this interference (Matese and Di Gennaro, 2015).
Drones (UAV) are able to fly autonomously via GPS system or can be controlled by a pilot on the ground. These platforms allow to obtain high resolution images from a large area with the possibility of timely monitoring (Matese and Di Gennaro, 2015).

3.2.2 Proximal sensing

Proximal sensing allows the acquisition of data using monitoring sensors much closer to the objects when compared to remote sensing. These sensors can be used individually or on moving vehicles, such as tractors, quad, robots, with or without an operator (Matese and Di Gennaro, 2015).
Proximal sensing technologies are able to collect data concerning not only the canopy upper part but also its sides with a high resolution. It can be used for several aims such as yield monitoring, canopy reflectance, berry composition, plant vigour, berry temperature, vegetation appearance and plant sensors like dendrometers and sap flow sensors to evaluate plant water status (Matese and Di Gennaro, 2015). Furthermore there are also other tools that are purposive for the evaluation of grape quality and composition, for example the Spectron (Pellenc SA, Pertius Cedex, France), which is a non-destructive tool based on optical sensors with integrated GPS, carried by an operator in order to monitor grape ripening (sugar concentration, acidity, anthocyanin concentration and water content) (Matese and Di Gennaro, 2015).
Another tool is Multiplex (ForceA, Orsay Cedex, France) (Fig.1), an optical sensor that uses fluorescence to determine the concentration of flavonols, anthocyanins, chlorophyll and nitrogen (Cerovic et al., 2008).

Figure 1. Multiplex hand-device sensors for quality of grape (Matese and Di Gennaro, 2015)

3.2.2.1 Cameras

Proximal sensing includes several cameras which are widely used in vineyards, for example for yield estimating by image analysis.

These cameras can be RGB, hyperspectral or multispectral and thermal cameras, mounted on a platform or used by a human operator (Lopes et al. 2017).

The cameras are sensors that collect information in an image thanks to (Fox et al., 2012):

- A lens (dioptric part) which concentrates the light and projects it on an image plane
- A mechanical or electronic shutter that monitors the duration of the exposure of the recording medium (film, plate or sensor)
- The diaphragm which allows the entry of light into a more or less partial way.

Initially images were loaded on a film and described by elements such as lines or polygons, a process that was expensive, slow and imprecise. Nowadays images are digitalized, that is composed of a series of points called pixels which measure the brightness of the reflected light. The quality of the images depends on their resolution, defined as the ability to distinguish two near objects on an image (Jones et al., 2010). The data collected for precision agriculture derive from images collected by different types of cameras.

RGB cameras describe the range of colors present in the environment and in agricultural fields by combining red, green and blue colors. These RGB images are used for image analysis.

Multispectral cameras photograph the environment with a limited number of spectra in the visible and infrared spectrum. The main difference is that they are limited compared to hyperspectral cameras and they take different radiometric information beyond RGB.

Hyperspectral cameras produce images in hundreds of positions on the electromagnetic spectrum, therefore they are able to produce more vegetation indices than multispectral ones (Pedersen et al. 2017).

Thermal cameras provide images of the ambient temperature, working at a wavelength of 14000 nm and sensing the infrared radiation emitted by the surface of the object. They can be used to estimate water stress in plants, detect diseases, pathogens and for fruit ripening monitoring (Pedersen et al. 2017).

LiDAR (Light Detection and Ranging) functions like a radar. It can eventually produce an image based on the points of data it collected. It allows to measure the distance from a target by sending rapid pulses of laser light on a surface, while in the meantime a sensor detects the time taken by the laser light to reach this surface (Pedersen et al., 2017). Thanks to these sensors we are able to study the phenotypic variation by building three-dimensional models of plants (Pedersen et al., 2017), besides they can also be used to map crops and vineyards, thus determining the growth of the foliage, providing a georeferenced 3D reconstruction of each individual plant and generating maps of spatial variability related to the size of the canopy, directly correlated with the LAI (Leaf Area Index) (Matese and Di Gennaro, 2015).

3.3 Vineyard yield estimation

Yield forecasting is an important tool for making decisions about crop load adjustments and yield management in time, in oder to optimize plant growth and improve grape quality (Nuske et al., 2011b; Aquino et al., 2018; Di Gennaro et al., 2019).

The yield is influenced by several biotic and abiotic factors such as: location of the vineyards, weather conditions, soil types, availability of water and nutrients in the soil, cultivars, rootstocks, management practices and vine health. Moreover, different studies have stated that within the vineyard there is a spatial and temporal variability of the yield, however we can observe significant variation between the vines as well (Clingeleffer et al., 2001; Taylor et al., 2005; Sabbatini et al. , 2012).

For all these factors, yield estimation is very difficult and it is necessary to find a highly-precise and non-invasive method, which requires little time and labour.

Nowadays there are several methods available to estimate the yield in the vineyard. They can be applied during all the phenological phases, from bud burst to harvest, but these are mostly manual methods with all problems described in chapter 1.

Finally, there is a non-destructive and inexpensive way to acquire precise and detailed information on the vineyard that is image analysis, a technique used in recent years and which we are trying to improve. Vineyard yield estimation is considered effective if the difference with the final production is less than 15% (Kurtural, 2008), clearly more data collection increases yield precision during subsequent vintages.

3.3.1 Manual methods

A great problem for manual methods is given by the spatial variability in the vineyard because often the number of samples is not sufficient to have an accurate estimate of the yield (Nuske et al., 2014).

The number of samples depends on the variability and size of the vineyard, the greater these aspects are, the more samples are necessary to determine a forecast of the yield with a higher accuracy. For this purpose a great amount of samples is required, provided that it is a costly method and not always carried out by vine growers.

It is possible to apply these methods during all the phenological phases if historical data are used.

During the initial phase, namely the period between budburst and flowering, it is possible to make an early yield estimate considering the fruitfulness of the bud before budbreak (Clingeleffer et al., 2001) with the following formula (Eq. 2):

Eq. 2 Y [t/ha] = (IF season/ IF previous seasons) * Historical average yield [t/ha]

Where IF represents the bud fruitfulness index (number of inflorescences per shoot).

Yield forecasting is also possible by estimating the number of flowers, which can serve as prediction indicator for the number of berries before flowering but it depends very much on fruit set and berry growth (Clingeleffer et al., 2001). This is not an ideal method because it is very hard to count the number of flowers automatically.

Another method can be applied after fruit set, when the berries are in the pea size stage and it is based on counting the number of berries per bunch (Dunn, 2010).

The formula is as follows (Eq. 3):

Eq. 3 Y [g] = N. of vines * (Bunches/Vine) * (Berries/Bunch) * Berry weight [g] * Harvest efficiency

This method involves the determination of the number of vines, the estimate of the number of bunches per vine by counting the bunches, the assessment of the berries per bunches from the sampled bunches, the prediction of the average weight of the berries at the time of harvest through the use of historical data and at the end the harvest efficiency.

In general, the yield forecast is more accurate at veraison, when the bunch is already well developed and close to the harvest and many variables are no longer influential.

To predict the yield during this phenological phase, Clingeleffer et al. (2001), uses the berry growth factor, as showed in equations 4 and 6:

Eq. 4 Bunch weight harvest [g] = Bunch weight [g] * Berry growth factor

Eq. 5 Berry growth factor = Bunch weight at harvest $_{\text{(historical data)}}$ [g]/ Bunch weight $_{\text{(veraison)}}$ [g]

Another formula proposed by Clingeleffer et al. (2001), determines the yield as (Eq. 6):

Eq. 6 Y [t] = ((Average yield [kg]/ Vine) * (Total number of vines/ Vineyard))/ 1000

Many of these methods are very invasive and require a lot of time and labour with inaccurate results given by samplings not really representative of the variability present in vineyard. These methods are mainly based on sampling and on the manual counting of yield components, such as number of vines/ha, number of nodes/vine, number of shoot/node, bunch/shoot, flowers/bunch, berries/bunch, berry weight (Martin et al., 2003).

3.3.2 Airborne pollen method

Over time, other less invasive, faster and more precise methods have been developed which provide an estimate of the yield based on the pollen dispersed in the air, the tension in the trellis system and the automatic image analysis.

The use of the airborne pollen method allows the prediction of yield early in the season on large plots of vineyards and it works in particular at a regional scale. The yield forecast through this method is carried out during the flowering phase because it is based on a model that detect the quantity of pollen grains dispersed in the air. In addition this model takes into consideration other factors such as pre-flowering conditions, vigour and vine health (Besselat and Cour, 1996).

It is possible to adopt two different pollen methods, one is the Cour method while the other is the Hirst method. In the first one the pollen grains are trapped in filters exposed to the air for 3-4 days during flowering, which are made of gauze with an area of 400 cm^2, fixed vertically on a wind-vane that continuously directs the filters according to the direction of the wind (Cour, 1974).

The filters are replaced twice every week and analysed according to the Cour method (1974), expressing the concentration of pollen in the air as the number of pollen grains transported per m^3 of air and subsequently it possible to estimate the yield through an algorithm in which all the variants are inserted (Ribeiro et al., 2005).

The Hirst method expresses the daily determination of pollen in the air in ($P/m^3/day$).

In a study conducted in San Michele all'Adige (Italy), data were collected for a period of 5 years. The weather conditions were recorded, in particular the temperatures and rains occurring during the flowering phase in the light of the fact that rains negatively influence the flowering by decreasing the fruit set percentage (Cristofolini e Gottardini, 2000).

The advantage of the airborne pollen method is that it allows us to obtain an early yield forecast. Nonetheless, the fact it works on large areas has to be considered a disadvantage because it impedes to separate the pollen of the different varieties, the production areas and the specific vineyard plots. In regions with early flowering or a rainy post-flowering period and large interannual variations in water stress, additional parameters such as disease outbreaks and weather conditions after flowering should be considered (Cunha et al. 2003).

3.3.3 Trellis tension method

Trellis tension method (TTM) is a technique that measures the variation in tension of the trellis support wire on which the vines are trained (Blom and Tarara, 2009).
The increase in the tension of the wire is converted into a mass measure relative to the yield thanks to the following algorithm (Eq. 7):

Eq. 7 $Y_{t,c} = (Y_a / T_{t,a}) * T_{t,c}$

Where,
$Y_{t,c}$ = Forecast of the yield at any time "t" of the season,
Y_a = Yield from the previous year,
$T_{t,a}$ = Trellis wire tension at the time "t" from the previous year,
$T_{t,c}$ = Trellis wire tension at time "t" of the season.

Forecast of the yield, before flowering, is irrelevant because the variation in tension is attributable to the growth of the canopy, that is why the forecast must be done only after flowering when the variations in tension are attributable to the mass of the grapes. It must be considered that this technique has deficiencies provided by seasonal variability and by the influence of wind and temperature (Blom and Tarara, 2009). It also requires a high density of sensors and a high quality and well-maintained supporting wire infrastructure.

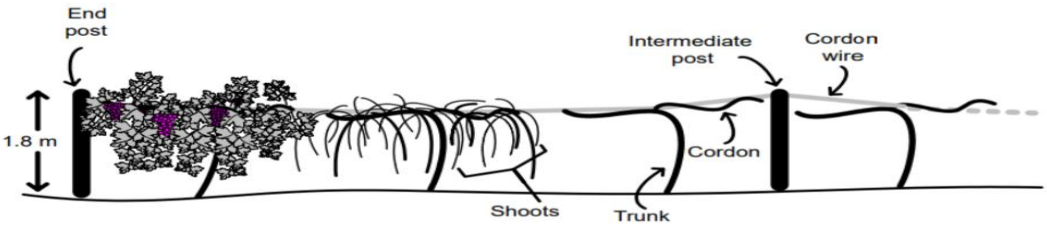

Figure 2. Schematic diagram of a vineyard row (Tarara et al. 2004)

3.3.4 Agrometeorological models

The agrometeorological models are guaranteed by the regression between the climatic variables measured during certain phenological phases, assuming that weather conditions, such as air temperature and rainfall, are the main factor of the yield variations.
The simulation of the crop describes its behaviour based on the weather conditions to which it is subjected. These models are not commonly used because they are very different, difficult to extrapolate (Gommes,1998), and they can be employed mainly at a regional scale.

3.3.5 Image analysis

Some of the methods previously described, like the manual method, are invasive and require a lot of time and labour, besides the fact that they are not very accurate. They can gain accuracy only if samplings are substantial and such methods are carried out on a regional scale. For these reasons, during the last decades, several studies have been focusing on the elaboration of images in order to create systems for estimating yield quickly, accuratly and repeatable several times (Diago et al., 2015). This development is mostly dependent on image analysis, that is to analyze the contents of digital images through the use of computer done in an automatic way (Glasbey et Horgan, 2001). Image acquisition in the field can be carried out manually (Diago et al., 2012a) or by mobile terrestrial platforms as robots (Lopes et al., 2017). During image acquisition, all images are subject to degradation, whether it be noise, blurring or distortion of the frame. To solve these problems it is possible to use filters to smooth or emphasize the edges, to reduce the size of the image and highlight the important parts for the final output (Glasbey e Horgan, 2001). One of the steps during the image analysis is the segmentation, namely the subdivision of the images into regions that correspond to different objects or parts of them, in which each pixel is assigned a number that corresponds to a region or a category of pixels (Glasbey e Horgan, 2001).
Image analysis is an important tool that allows to obtain data from the study of images or videos, in order to identify objects in images through the use of algorithms and different methodologies (Fuentes et al., 2008; Tardaguila et al., 2013; Victorino et al., 2020). Therefore, image analysis is used to derive yield components such as buds, flowers, clusters, berries, and cluster tracts at different phonological stages (Victorino et al., 2020).
An important problem that needs to be improved in the future is the lack of visibility of all the berries in a bunch due to the occlusion from other berries, leaves or other material from the vine. For this purpose it is necessary to work a lot on image analysis. In fact, this method is used more to determine the leaf area rather than the yield as the visibility of the grapes, in non-defoliated vineyards, is limited during ripening and harvesting (Diago et al., 2012; Fernandez et al., 2013).
Through the development of complex algorithms it is possible to perform an analysis of the images captured in the vineyard, thus obtaining an early estimate of the yield, provided that either a survey has been made on the number of flowers on the inflorescences or an estimate close to the harvest on the image of the bunches or berries (Millan et al., 2017).

3.3.5.1. Color spaces CIELAB, HSV

The most known and used image-acquisition method is the application of colour-based to detect grapes in images. This method is based on the separation of the RGB and HSV color space, and requires only one commercial RGB (Red, Green, Blue) camera (Diago et al., 2012; Fernandez et al., 2013; Liu et al., 2013).

Once RGB images are acquired, they are converted into the L*a*b* color space, known as the CIELAB (Fernandez et al., 2013). It is an international standard for color measurement developed by the Commission International d'Eclairage (CIE) in 1976 (Diago et al., 2014). CIELAB is represented by three coordinates (CIE Colorimetry, 1986; Tkalčič and Tasič, 2003; Wyszecki and Stiles, 1982) (Fig. 3):

- Brightness (L*): representing the brightness layer, which is between 0 and 100,
- Hue (a*) (b*): representing chromaticity, where a* indicates the color falling between the red-green axis, while b* indicates the color falling between the blue-green axis.

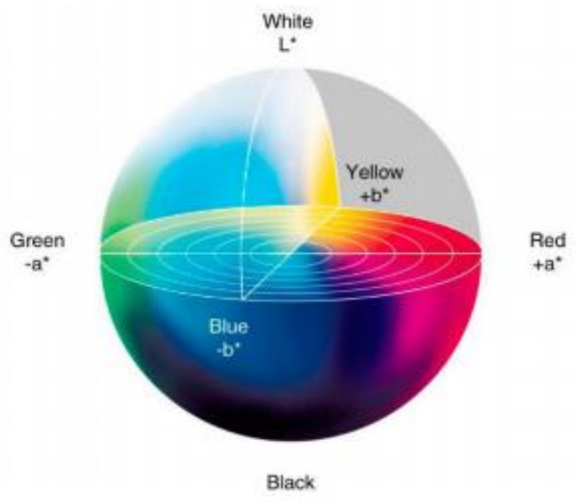

Figure 3. CIELAB colour space (Cortez et al., 2017)

This color space uses three attributes to describe a color: Hue, Saturation and Brightness (HSB) (Cotton, 1996; Tkalčič and Tasič, 2003):

- Hue: that is the color itself and indicates whether the color is red, green, yellow, blue.
- Saturation: indicates the level of color intensity and the level of non-whiteness.
- Brightness: shows the intensity of the light.

3.3.5.2. Image analysis to detect shoots

An early estimate of the yield in vineyard is of fundamental importance for growers as they can act promptly and appropriately in regulating the yield.

In the work conducted by Liu et al. (2017) the aim was to estimate the yield by developing an automatic system for counting the shoots before fruit-set. Specifically, a shot detection framework was used in combination with an algorithm.

The data were collected during day-time in the form of video of shoots with different adversities to overcome: change of shoot position in the field of view, changes in light conditions, reflections, shadows, objects that obstructed the view such as cord, poles, wires, etc... To solve these problems, the images from the video were divided into sub-windows and processed as object candidates. The segmentation method that allowed images to be converted into binary using a threshold value could not be applied, due to variations in lighting conditions during video shooting. A dynamic threshold method proposed by Otsu (1979) was therefore used and considering that the prediction was made before fruit set, excellent results were obtained.

3.3.5.3. Image analysis to estimate the flowers

The number of inflorescences and flowers are very important yield components to estimate the yield however it is difficult to estimate them due to different variables such as the phenological phases of flowering and fruit-set, which influence the yield and consequently its estimate as they define the number of berries per bunch.

Fruit-set has varietal and clonal variability and is affected by physiological, environmental and pathological factors, for this reason it is possible to obtain an accurate estimate of the fruit-set by counting the flowers per inflorescence by image analysis. This current method is more economic, rapid and simple if compared to the manual one with the aim of improving forecasting in early stages.

In a study carried out by Diago et al. (2014) (Fig. 4), RGB images captured in the vineyard were used to estimate the number of flowers per inflorescence and analysed by MATLAB. The method for counting flowers was divided into three stages:

- Pre-processing of images captured in vineyard by converting them from RGB colour space to CIELAB,
- Counting of flowers which correspond to the brightest areas because their surface reflects more light,
- Removal of material that does not match with the flowers from the brightest area selected.

The authors then compared the software results with those obtained by manual counting of the number of flowers.

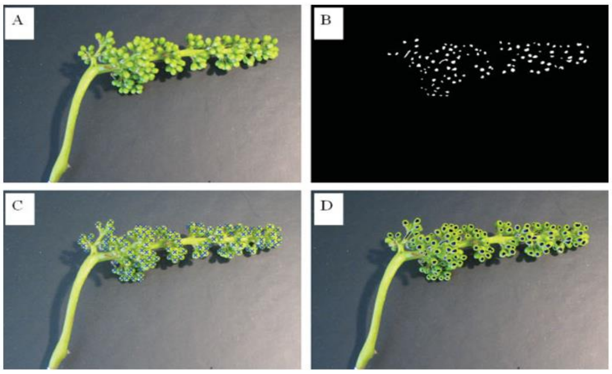

Figure 4. (A) Raw RGB image; (B) same image with flowers manually marked with an 'X'; (C) same image after the segmentation process; and (D) raw RGB image combined with the regions detected (dark points) after the automatic counting of one representative inflorescence of cv. Graciano at phenological stage BBCH 55 (Diago et al., 2014)

In another study developed by Rudolph et al. (2018) (Fig.5), also based on the counting of the number of flowers per inflorescence, the approach was different. The images were captured in the field without a background and the work was divided into four stages:

- Capturing images using a camera,
- Identification and localization of inflorescences by segmenting images,
- Flower extraction,
- Evaluation of the resulting phenotyping data.

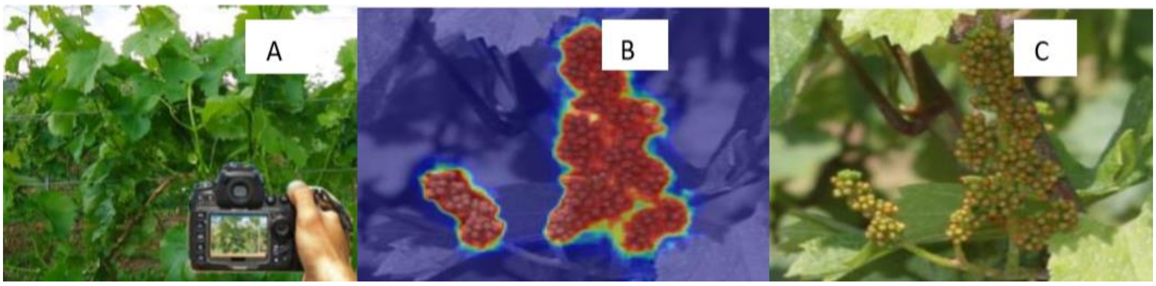

Figure 5. Workflow of flowers detection: data acquisition (A), segmentation of images into "inflorescence" and "non-inflorescence" (B), flower extraction (C) (Rudolph et al., 2018)

Aquino et al. (2015) began studying a new Android application, vitisFLOWER ®, for automatic flower counting. This method is applied in the vineyard and is not invasive. You can take a picture with the smartphone camera and then the application analyzes the images, detects and counts the flowers with a simple click. This procedure is allowed by an algorithm of image analysis based on mathematical morphology and pixel classification. However, you need to take the photo by placing a dark background behind the bunch.

3.3.5.4. Image analysis to estimate the bunches and berries

The aim of the following works is to develop a method for the determination of the number of berries and bunches that is fast, accurate, simple and economic (Diago et al., 2014).

In the study carried out by Grossetete et al. (2012) the images were analysed with the aim of counting the number of berries, from flowering to veraison and they were taken by the smartphone camera. An integrated flash is used for the analysis of the images, this is because the surface of the berries reflects the light and the maximum reflection point is on the middle of them. The images were analysed with an algorithm based on the correlation between the Gaussian profile and the proximity of each pixel, making up the correlation maps. On each berry the reflection area corresponds to the white pixels but on the same berry we can have more specular areas and subsequently a morphological dilation is performed in order to solve this problem. In the end the authors obtained the number of visible berries.

In the study conducted by Aquino et al. (2017) (Fig. 6), the number of berries per bunch was estimated by analysing 2D images. The RGB images were captured with a smartphone camera, they were converted into the CIELAB color space and once determined the region of interest (ROI), by colour discrimination using a dark background, it was analysed. The berry-segmentation algorithm on MATLAB was used. In this way a series of potential berries were detected by means of the luminous points produced by the reflection of light on the surface of the berries. ROI also includes errors or other components, such as the rachis A filter was used to discard these errors, in fact the candidates not corresponding to the berries, the so-called false positives, were discarded.

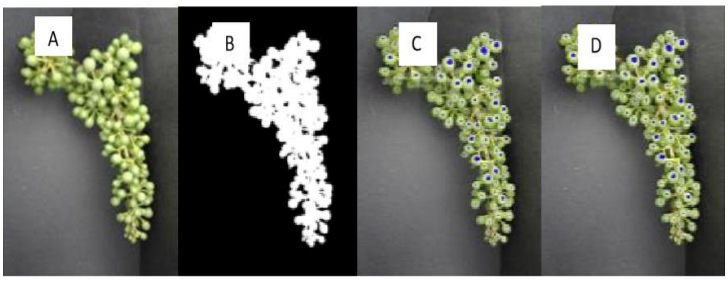

Figure 6. Example of the application of the methodology for berry segmentation. Original RGB image (A), ROI extracted (B), Berry candidates (C), Final result obtained after filtering false positive (D) (Aquino et al., 2017)

Still with the aim of estimating the yield of the vineyard, a work was carried out using 3D images obtained from 2D images taken from the field, detecting the number of grapes and the weight of the bunch. The images of the bunches in 3D were obtained with Photogrammery Workbench, a software developed by the authors of the work (Herrero-Huerta et al., 2015). For this work, the difficulties involved are of two kinds: visibility of the bunch side only and the occlusion and geometric complexity of the bunches. To solve these issues, it was important to acquire image elements such as their position, as it could have influenced the final accuracy and completeness in terms of overlap between 3D images.
In Zabawa et al. (2019), a field platform based on a grape harvester called Phenoliner, was used to capture the images. From the images the berries were detected through an automatic detection pipeline based on the classification of three classes: "berry", "edge" and "background" and the application of a neural network. Each berry was coloured with one of the four colours and an edge with a certain size. The number of berries was determined using an algorithm. This classification has allowed the differentiation between the berries of the bunch, the identification of the position, the count but also the investigation of their size. In the end, the study estimated a number of berries with an accuracy of 94% in the VSP system and 85.6% in a semi-minimal hedge (SMPH). This difference is due to a greater occlusion of the grapes from the canopy in SMPH, while in VSP, the berries are positioned at the end of the canopy and are not very occluded.
Coviello et al. (2020) developed a smartphone application for yield estimation called Grape Berries Counting Net (GBCNet). The images are captured directly in the field without special precautions or contrast tools, through the smartphone camera and processed by the application, obtaining a density map. After that the number of berries is estimated through deep learning algorithms. The average error for berry detection was 5%, but if more than three images of the same plot were to be analyzed this value could decrease.
The work performed by Liu et al. (2020), is useful to count the berries through the use of an algorithm without calibration in the field for a quick estimate of the weight of the bunch. This method in addition to berries estimation allows to determine the 3D structure of the bunch. The work was performed on both red and green grapes, on bunches with different architectures and in any phenological phase, from pea size to harvest.
The images were obtained using the camera of a smartphone directly in the field. The original photo was cropped and segmented from the background. The berries on the edge were mounted following the curvature of the berry while the remaining berries were positioned inside the outline. The number of berries was estimated through an algorithm and the scarcity factor was introduced in order to avoid an overestimation of the berries caused by the 3D model that had not taken into account the empty space inside the bunch before.

The precision of the algorithm was 89% when compared directly with the number of berries in the bunch, on the other hand, when multiple images were considered, the accuracy was over 99%. The processing time per image is very fast, equal to 0.1-1 s, therefore it is considerably faster than manual counting and other existing methods and it does not require any kind of human interaction once the image has been captured. Liu et al. (2020b) developed a smartphone application called 3Dbunches based on the algorithm mentioned in the previous work (Liu et al., 2020a). This app recorded 91% accuracy.

In a research study by Nuske et al. (2011a) the estimate of the yield was performed before veraison by acquiring images thanks to an RGB camera and an artificial lighting mounted on a vehicle. The image analysis used an algorithm that allowed to detect the potential position of the berries with the radial symmetry transformation (Loy and Zelinsky, 2003) which used the circular shape of the berry to detect it. The next step was to identify the grape and non-grape points and groups of the nearby berries in bunches. In the end the authors compared the estimate of the number of berries with the weights of the harvest, demonstrating that it was possible to obtain an estimate of the yield with an error of < 9,8% from the real weight by analysing the shapes and texture of the berries (Doutor et al., 2018).

During a study by Tardáguila et al. (2012), yield and total leaf area determined through image analysis were evaluated. The authors used a digital camera to acquire the images from randomly chosen, defoliated and thinned vines in several steps and a white background to avoid noise from the grapevines of the close row.

The images were made before and after any defoliation and bunch thinning and they were cut to include only the canopy portion correspondent to the grapevines and in the end they were analysed by MATLAB program (Mathworks, USA), which selects user-defined pixels on the images, for an algorithm based on the Mahalanobis distance (Tardáguila et al., 2011). The program establishes classes such as bunches, green leaves, withered yellow leaves and porosity of the canopy, counting the total number of pixels for each class.

To reach more accurate results it would be advisable to have bunches more exposed and not occluded by other organs of the plant, this is because the more the bunches are exposed the better they can be seen by the sensors. In this regard, the concept of canopy porosity is important, by which we mean the percentage of empty spaces in the canopy. It is a relevant factor as it lets the bunches to pick up the light, shade, airflow (reducing the risk of fungal infections, Austin et al., 2011), the synthesis of aromatic compounds (Reynolds and Wardle 1989; Diago et al., 2010) and phenolic compounds as anthocyanins (Bubola et al., 2012, Diago et al., 2012b).

To evaluate the canopy porosity the Point Quadrat analysis (PQA) (Smart 1987) is employed, which is a laborious, lengthy and dangerous technique to the grapes. It consists in putting a probe into the canopy (perpendicularly) and counting the parts of the vines that are in contact with the probe (bunches, leaves, canes or graps).

Lopes et al. (2017), used a robotic platform, called VINBOT, to estimate yield and the canopy features. The authors manually assessed the canopy size and yield (number and weight of the bunches) and then performed the scan using VINBOT. Afterwards they analysed the images obtained using an image analysis algorithm (ImageJ 1.48V). The area in the image occupied by the bunches was calculated in pixels and converted into cm^2. This area was subsequently converted into kilograms. The yield estimated by VINBOT was compared with the actual yield and although proving an acceptable performance for the estimation of the canopy features, it produced an underestimation of the yield mainly due to bunch occlusion.

These are some of the image analysis methods that have been developed in recent decades, which need further work in the following years.

3.3.5.5. Image analysis to detect bunch traits

For the yield forecast in the vineyard, features of the bunch such as area, volume, ecc... must be analysed in addition to the above-mentioned yield components as shoots, flowers, bunches and berries (section 3.3.5.2; 3.3.5.3; 3.3.5.4.) (Font et al., 2015; Herrero-Huerta et al., 2015).

In studies conducted by Font et al. (2015) and in Hacking et al. (2019), the bunch area was determined by estimating the volume and number of pixels in the segmentation image, while in the study performed by Herrero-Huerta et al. (2015) the bunch volume was determined thanks to the 3D reconstruction of the bunches.

In these studies the ratio between the bunch area and the volume were converted into the weight of the bunch obtained from their relationship (Lopes et al., 2016) and thanks to the high correlation between bunch area on the volume and weight of the bunch (Font et al., 2015; Hacking et al., 2019), these bunch traits can be used for yield estimation as Victorino et al. (2020) did.

4. MATERIALS AND METHODS

For carrying out this thesis work, due to the COVID-19 pandemic, I was not able to personally set up the work from the early stages, neither in the vineyard nor in the laboratory. To overcome these problems, we made use of the work done by ISA research team during the 2019 growing season and used the images and data collected in the vineyard and in the laboratory.

4.1. Site description

The experiment was carried out during the 2019 vintage on the Encruzado grapevine cultivar (Vitis vinifera L.) in the experimental vineyard located in the Instituto Superior de Agronomia (ISA) (Tapada da Ajuda, Lisbon, Portugal) (38°42' N, 9°11' W) (Fig. 7).

Figure 7. Map captured from Google Earth showing the ISA vineyard, located in Lisbon, Portugal, where the studies were conducted

The vineyard has an area of 1.7 ha, it encompasses a slope ranging from 7% to 9% and north-south row orientation and is located about 50 m above sea level. The vineyard was planted in 2006 with the following varieties: Alvarinho, Arinto, Moscatel de Setubal and Viosinho grafted on rootstock 1103 Paulsen (1103 P) (Vitis berlandieri x Vitis rupestris) and Encruzado, Macabeu and Moscatel Galego grafted on rootstocks 110 Richter (110 R) (Vitis berlandieri x Vitis rupestris), this second rootstock is very vigorous with a tendency to induce high productivity to the varieties in which it is grafted. The vineyard is irrigated. Water was supplied with a drip irrigation system and irrigation was managed using a soil water probe. Irrigation provided about 50% of crop evapotranspiration from flowering to harvest.

The distance between the rows is 2.5 m and the distance between the vines is 1.0 m, with a density of 4000 plants/ha. The trunk of the vines has a height of around 0.70 m and the vines are trained to a vertical shoot positioning trellis with two pairs of movable wires, and spur pruned on an unilateral Royat cordon system. The vines have an average of 5-6 spurs with 2-3 buds. Thus, the number of buds can be estimated at about 45.000 buds/ha.

The soil of the vineyard is a clay loam with approximately 1.6% organic matter and a pH of 7.6 (Teixera et al., 2018). It is described as a reddish-brown clay, not basaltic limestone. It presents a profile of type Ap (B) C characterized by a high content in colloids of montmorillonite, which gives it a high plasticity when wet and hard when it is dry; it can be cracked when the moisture content is very low. The expandability and the field capacity values are high with a usable capacity in the first 0.50 m. Its permeability is rapid to moderate (Sarmento, 1969).

The cultural practices applied during the biological cycle are the same for all ISA vineyards, which are standard practices and followed by a team of technicians from the Instituto Superior de Agronomia (ISA). Regarding the management of the soil an herbicide undervine is applied, while a cover crop of resident vegetation is used between the rows.

4.2. Climate characterization

According to Thornwaite characterization, based on the global index of humidity (Thornthwaite, 1948), the climate in Tapada da Ajuda is mesothermic, with moderate rainfall in winter and deficit in summer. The average annual rainfall (1971 to 2000) is 725.8 mm and the average annual temperature is 15.4°C (IPMA, 2019), with a maximum annual value of 39°C and a minimum annual value of 5°C. The Figure 8 shows the evolution of precipitation and average monthly temperature at Tapada da Ajuda during the 2019 season. Rainfall have been below the average for 30 years.

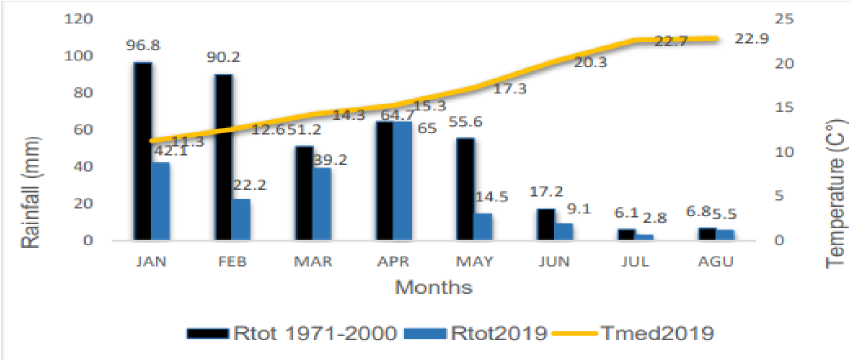

Figure 8. Accumulate rainfall (Rtot) and average temperature (Tmed) during 2019 growing season (IPMA 2019).

4.3. Encruzado characteristics

The Encruzado variety is a native Portuguese variety cultivated in about 300 ha, mainly in the Dão region and it represents about the 0.15% of the total area of vineyards in Portugal (Bohm, 2010). The bunches are medium-small and medium compact, cylindrical shape and with short peduncles. The berries are medium, difficult to detach, heterogeneous and slightly flattened and their epidermis is yellowish green. The pulp is soft and succulent and it has a very unique flavour (Bohm, 2010).

The adult leaf is small, pentagonal, dark green and bright, the bottom page is hairless and the petiolar sinus little open to V, like the upper side sinuses (Bohm, 2010) (Fig. 9).

Figure 9. Leaf and bunch of Vitis vinifera Encruzado (Bohm 2010)

The Encruzado variety has an erect behaviour of the shoots, it is characterized by a high vigour and a tendency to lateral shoots development with usually medium-short internodes, frequently presenting tendrils from the third internode. This variety is adaptive to any type of pruning but the shoots positioning is very difficult to apply (Bohm, 2010).

The yield is in average regular and it is very susceptible to strong winds and it has a good aptitude for mechanical harvest (Bohm, 2010).
It is suitable for hot and dry regions, rocky soils and low fertility, however, it tends to delay the ripening of grapes and colour in the most sensitive varieties when the soils are very fertile or humid (www.vivairauscedo.com/portinnesti).

4.4. Vinbot platform

The Vinbot robot platform is based on a Summit XL HL mobile base able to carry up to 65 kg payload and consists of (Fig. 10) (Lopes et al., 2017):

- A robotic platform: durable, mobile, initially developed in ROS Indigo Igloo, currently in ROS Kinetic Kame;
- RGBD Kinect v2 camera to take images of the vine;
- 2D range finders to navigate the field and to obtain the shape of the canopies;
- A small computer for basic computational functions, connected to a communication module that use Bluetooth and Wi-fi;
- An optional RTK-DGPS high-accuracy rover, optional base and associated communication devices;
- A cloud-based web application to process images and create 3D maps;
- User friendly human machine interface (HMI) to define navigation and data acquisition missions.

The RGBD Kinect v2 has two cameras, the RGB camera collects images with a resolution of 1920x1080 pixels, whereas the IR camera is used for the real-time acquisition of depth-maps and IR data with a 512x424 pixels resolution.
The Vinbot is an unmanned mobile robot capable to navigate autonomously over rough terrain and to climb slopes up to 45º with an electric battery capacity of up to 8 hours to photograph and digitize the rows of vines. Although it collects only data through the LiDAR (Laser Rangefinder) system and the RGB-D camera, the mobile platform can incorporate numerous other sensors and technologies (www.vinbot.eu).

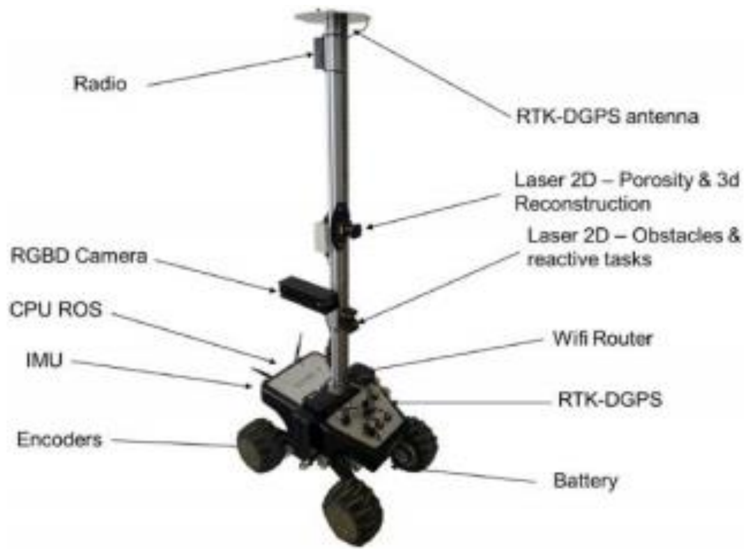

Figure 10. Vinbot component sensor and component distribution (Guzman et al., 2016)

4.5. Experimental design

In the ISA vineyard, during the 2019 season, 4 smart points (SPs) were selected for data collection (Fig. 11). These SPs were groupings of adjacent vines along a row, chosen randomly, in order to understand the spatial variability along the vineyard and the rows as much as possible. The first smart point (SP1) was in row number 41, the second one (SP2) was in row 43, the third one (SP3) was in row 45 and the fourth one (SP4) was in row 48.

For each smart point they took into consideration 25 linear canopy meters (LCM), divided into: 10 meters for the Vinbot data collection during all the growing season; 15 LCM were dedicated to the image collection with a manual RGB camera (Nikon D5200) for three phenological stages: 5 LCM for pea size (Phenological phase whose data were not used in this thesis), 5 LCM for veraison and 5 LCM for maturation. The LCM dedicated to Vinbot were delimited with a meter scale (divided in steps of 0.10 m) fixed on the vines to have the same vine reference in the images every time. Regarding the others 15 LCM they used a transportable scale that they fixed on the vines, because it had to be used once for each 5 LCM, in the corresponding smart point and phenological stage.

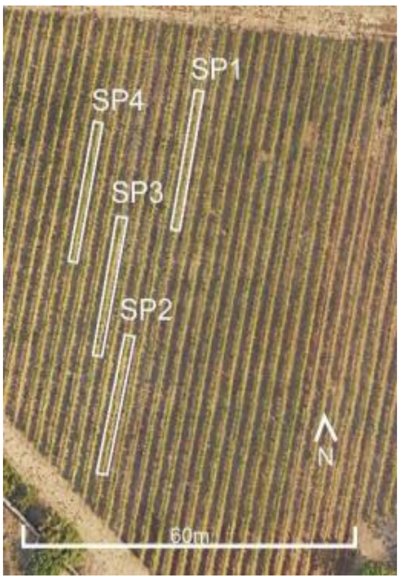

Figure 11. Partial Map from Google Earth with the location of the four Smart Point (SP) used for data collection

4.6. Image analysis

The image analysis conducted in this work can be divided into three separate datasets: Manual lab images (1), Manual field images (2) and Vinbot field images (3). All images were collected during the 2019 season by the ISA research team (Mauro, 2019). Each dataset was collected in different conditions and encompassed a total of 109, 90 and 80 images, respectively. In all three datasets, the number of visible berries was counted manually with the help of a program developed in MATLAB (Abbreviation of Matrix Laboratory) to facilitate this laborious task. The version R2010b of MATLAB was used. The program tracks the berries already counted and provides a sum of all counts in the end. The counting was performed manually without the aid of an automatic algorithm, simply by clicking each berry in the image, thus producing an estimate of visible berries with the highest accuracy possible. These data were then used to estimate grapevine yield using the Vinbot platform. In the following sections, each data set will be explained in detail.

4.6.1. Laboratory detailed measurements

During the veraison and in the full maturation phases, the bunches of only one LCM were chosen for each SP, SP1, SP2 and SP3, for the laboratory detailed measurements, with the exception of SP4. The bunches were individually picked from the vineyard, identified with labels (Fig. 12) and taken to the laboratory to be photographed using the same manual RGB camera as the one used in the vineyard. A total of 109 bunches were harvested, 56 at veraison and 53 at maturation.

Figure 12. Bunch of Vitis vinifera Encruzado during the 2019 season

Two pictures for each bunch were collected featuring front and side perspectives with a blue background. To maintain the same distance from the bunch, the camera was mounted on a tripod and moved, between position references present on the floor as to take two pictures. 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.
Then the bunches were weighed (BW) using a digital table scale (KERN FCB version 1.4), the actual bunch volume (ABV) was determined and the berries were separated, photographed and then weighed without the rachis (Fig. 13), in order to analyse berry weight and size individually and to estimate the berry growth factor (from veraison to harvest).
After berries detachment, the rachis and wings (if present) length were assessed, using a ruler meter, scaled in millimetres.

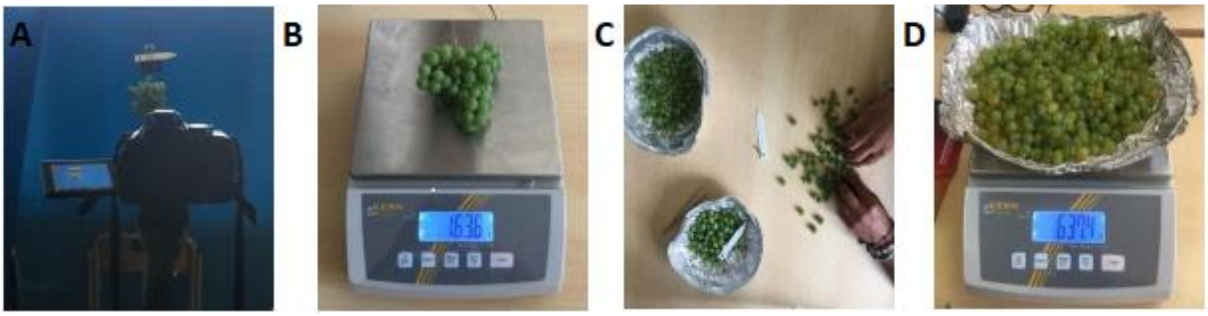

Figure 13. The detailed measurement performed in the laboratory: (A) the blue background used to take the pictures of the bunches, (B) the scale used to weight the bunches, (C) the berries separation, (D) the weight of the berries for the 2019 Encruzado variety

Thanks to the weight of the berries (g) (bW) obtained in the laboratory, we determined the average weight of each individual berry (g) (AbW) for each bunch with the equation 8:

Eq. 8 AbW [g] = Total berries weight [g]/ Total berry number (Tb_L)

Afterwards we identified the average total weight of the berry for both veraison ($AbW_{(Veraison)}$) and the harvest ($AbW_{(Harvest)}$).
In laboratory, the RGB images of each bunch captured by two different perspectives, were manually analysed by MATLAB software, with the aim of counting the total number of visible berries at bunch level (Vb_B) with a simple click on the berry, thus determining for each bunch, the Vb_B in two different perspectives: “Vb_B side A”, which corresponds to the front bunch, and “Vb_B side B” which corresponds to the side bunch. Then the average Vb_B was calculated as the average visible berries from side A and B, for each bunch (Fig. 14).

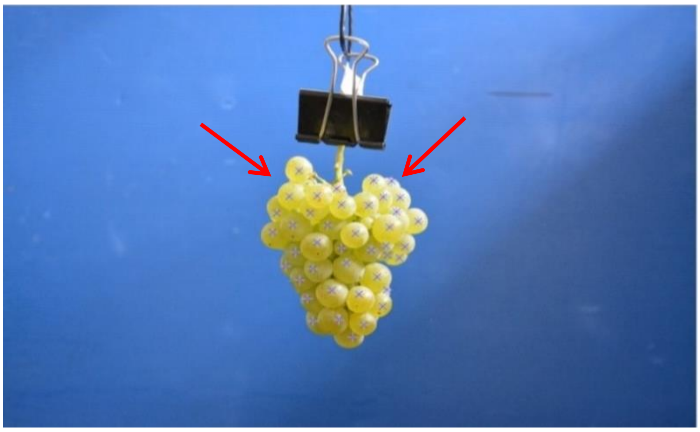

Figure 14. Bunches on blue background photographed in the laboratory analysed with MATLAB (Image credit Gonçalo Victorino)

Berries can occlude other berries and this occlusion represents a degree of uncertainty for the yield estimation since it impedes the complete visualization of all the berries in a bunch. For this reason, the average percentage of berry occlusion was calculated in order to have a better yield estimation.

This last parameter, "Average Vb_B", allows to obtain the % of visible berries in laboratory (% Vb_L) (Eq. 9):

Eq. 9 % Vb_L = (Average Vb_B/ Tb_L) * 100

With the equation 9 it was possible to obtain the average percentage of occlusion of the berries by other berries (AbO_b) (Eq. 10):

Eq. 10 AbO_b [%] = 100 – (Average % Vb_L)

4.6.2. Estimation of berries covered by leaves

The fraction of visible bunches, and consequently of berries, depends on the porosity of the canopy, indeed the leaves can occlude the bunches and affect their capability of being seen by the cameras, thus influencing the accuracy of the yield estimation. The canopy porosity was calculate in percentage, the higher the % of porosity, the higher the % area of visible bunches is and consequently an increase in the visible berries.

To study this relationship, during the phenological stages of veraison and full maturation, RGB images collected with a commercial RGB camera (Nikon D5200), were used in order to calculate the total number of berries in a LCM.

Images were acquired in three different steps of defoliation (Fig. 15):

- Step 1: Picture with all the existing leaves (no defoliation);

- Step 2: Picture with a low defoliation for SP1, medium defoliation for SP2, high defoliation for SP3 and a mix of the three defoliations for SP4;
- Step 3: Picture with complete defoliation of the fruiting zone.

Figure 15. Different vines with different levels of defoliation from left to right: low, medium and high defoliation degrees (Image credit Gonçalo Victorino)

To have an homogeneous background and to facilitate the analysis, a blue background was placed behind the canopy. All captured images were analysed with MATLAB software (Fig. 16).

Figure 16. Analysis with MATLAB of RGB images to determinate the total numbers of berries in a linear canopy meter (Image credit Gonçalo Victorino)

The percentage of visible berries at vine level (Vb_v) was obtained using Eq. 11:

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

This technique was used to induce different levels of defoliation, in order to allow a wider range of bunch exposure. The aim was to simulate different porosity realities and relate that trait with the percentage of visible berries, which should increase with a lesser amount of leaves.

4.6.3. Vinbot dataset

During the phenological stages of veraison and maturation, the RGB images of the VINBOT platform were obtained from all four 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 m.

To make image analysis easier and to avoid background noise from adjacent rows, a blue background was placed behind the canopy. As its 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.

At maturation, in all the four SPs, the bunches were collected from the analysed vines as to obtain the actual yield. On each acquired image (Fig. 17), using image analysis, 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). These data were used in this present research for further evaluation. In the same images, the berries were manually counted, considering an LCM, as described in section 4.6.1.

Figure 17. RGB image captured by VINBOT in the vineyard using a blue background (Image credit Gonçalo Victorino)

Yield was estimated on images of non-defoliated vines, collected by the Vinbot platform (Fig. 17). 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 (P %) and % Visible berries, estimates the proportion of visible berries that are being occluded by vegetation (% Vb; Eq. 12, 13):

Eq. 12 $\% Vb = - 0.0184 * (P \%)^2 + 2.5444 * (P \%) + 14.013$ (Veraison)

Eq. 13 $\% Vb = - 0.0212 * (P \%)^2 + 2.7564 * (P \%) + 11.004$ (Maturation)

Using the measured number of visible berries (Vb_v) we obtain the estimation of total number of berries that would be visible if all leaves were removed (Vbtot; Eq. 14):

Eq.14 $Vbtot = (Vb\_v / \% Vb) * 100$

This result does not include the total number of berries yet, 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 Vbtot from a 2D perspective (Eq. 15 and 16):

Eq.15 $btot = 1.6486 * Vbtot – 10.024$ (Veraison)

Eq. 16 $btot = 2.2673 * Vbtot – 33.14$ (Maturation)

After applying both models the estimated yield (Yest) was obtained by multiplying the estimated total number of berries by the average berry weight (AbW), obtained at harvest using the laboratory data, (Eq. 17):

Eq. 17 $Yest\ [kg] = (btot * AbW\ [g]) / 1000$

This estimated yield was then compared with the actual yield (Y) and the percentage of error (% E) was determined with equation 18:

Eq. 18 $\% E = ((Yest\ [kg] – Y\ [kg]) / Y\ [kg]) * 100$

4.7. Data analysis

All data analysis were performed both at veraison and maturation, using different statistical tests 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).

5. RESULTS AND DISCUSSIONS

5. 1 Laboratory data

Table 1 shows that the Encruzado variety presents an increase in BW and bW in the period from veraison to maturation, as well as the AbW. The increase in the BW and bW during the vegetative cycle was evident and expected as it was caused by the changes in either the bunches and berries size from veraison to harvest, in fact, if we look at the ABV, it increases from veraison to maturation.

The Tb_L did not undergo any statistical difference between veraison and maturation, for instance if we observe 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 due to the fact that the bunches were randomly slightly smaller but the number of the berries did not vary.

The Vb_B side A and side B, and consequently the average Vb_B, determined by image analysis, decreases from veraison to maturation, this is probably related to the increase in the size of the berries in the period that elapses between the two phenological phases, which occlude other berries and hinders detection by means of the image analysis. This is also demonstrated by the increase in percentage AbO_b at maturation and on the decrease in Vb_L (%), compared to veraison.

Table 1. Summary statistics of measured and calculated variables, at veraison (n=56) and maturation (n=53), for each bunch of the cultivar "Encruzado": bunch weight (BW), berries weight (bW), average berry weight (AbW), actual bunch volume (ABV), total number of berry "laboratory" (Tb_L), visible berries in a bunch side A (Vb_B side A), visible berries in a bunch side B (Vb_B side B), average visible berries in a bunch (Average Vb_B), % of visible berries "laboratory" (Vb_L), % average berry occlusion by other berry (AbO_b).
Avg: average ± standard deviation; Max: maximum value; Min: minimum value.

Bunch and berry attributes	VERAISON			MATURATION		
	Min	**Avg**	**Max**	**Min**	**Avg**	**Max**
BW (g)	15.9	122.4 ± 51.2	267.7	35.2	151.3 ± 102.7	425.6
bW (g)	15.4	119.6 ± 50.3	265.8	20.3	144.5 ± 98.7	406.2
AbW (g)	0.7	1.4 ± 0.4	3.4	1	2 ± 0.4	2.9
ABV (ml)	20	119.3 ± 49.1	255	20	138 ± 94	390
Tb_L	9	89.5 ± 34	169	9	71.5 ± 45.6	218
Vb_B side A	9	63.9 ± 19.7	106	13	48 ± 21.9	113
Vb_B side B	9	56.2 ± 15.2	87	13	44.3 ± 17.7	89
Average Vb_B	9	60 ± 17.1	93	13	46.1 ± 19.5	101
Vb_L (%)	31.2	71.3 ± 13.8	115.2	46	75.7 ± 22.8	144.4
AbO_b (%)	-	28.7 ± 13.8	-	-	24.3 ± 22.8	-

5.1.1. Effect of bunch side on visible berry number

The one-way ANOVA Test for comparing the number of the visible berries between side A and side B conducted at both veraison and maturation produced different results. At veraison the F test was < 5%, therefore we cannot accept the null hypothesis, consequently we have significant differences between the visible berries on side A as compared to side B. At maturation no significant differences between the visible berries on side A and those on side B were observed.

5.1.2. Correlation analysis for laboratory data

Table 2 shows that the Average Vb_B presents a very high and significantly positive r with the BW and Tb_L, at both phenological stages but higher at maturation.
For what concerns Tb_L, it presents a high and significantly positive r with the BW for the two phenological phases and, as observed previously, at maturity r was higher than at veraison.

The high and significant correlation coefficients obtained indicate that these variables, if accurately detected, can be used as good explanatory variables for estimating grapevine yield, in fact, regarding the Tb_L and Average Vb_B, it is widely know that they explain a significant percentage of bunch weight (Clingeleffer, 2001). Indeed, the use of the number of berries by several authors shows that this variable is an excellent explanatory of wine yield (Diago et al., 2015; Grimm et al., 2018; Millan et al., 2018; Nuske et al., 2014; Zabawa et al., 2019). The results obtained in this research (Table 1) confirm that the Tb_L can be used as a good explanatory of BW if all berries are visible, but since with the moving yield estimation systems used, not all berries are visible, so they must 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 "Encruzado" variety. The set of variables include: bunch weight (BW), total number of berry "laboratory" (Tb_L), average visible berries in a bunch (Average Vb_B).

	VERAISON			MATURATION		
	BW (g)	Tb_L	Average Vb_B	BW (g)	Tb_L	Average Vb_B
BW (g)	1			1		
Tb_L	0.78***	1		0.97***	1	
Average Vb_B	0.80***	0.83***	1	0.96***	0.97***	1

*** indicates significance at P ≤ 0.001.

5.1.3. Relationship between the total berry number and average number of visible berries

The linear regression models had a good coefficients of determination but different for the two phenological phase, 0.69 and 0.94 at veraison at maturation respectively (Fig. 18). The linear regression analysis showed highly significant results for the two phenological phases, therefore the model can be used to estimate the total number of berries especially at harvest. So the average number of visible berries explains 94% of the total variability of the number of berries.

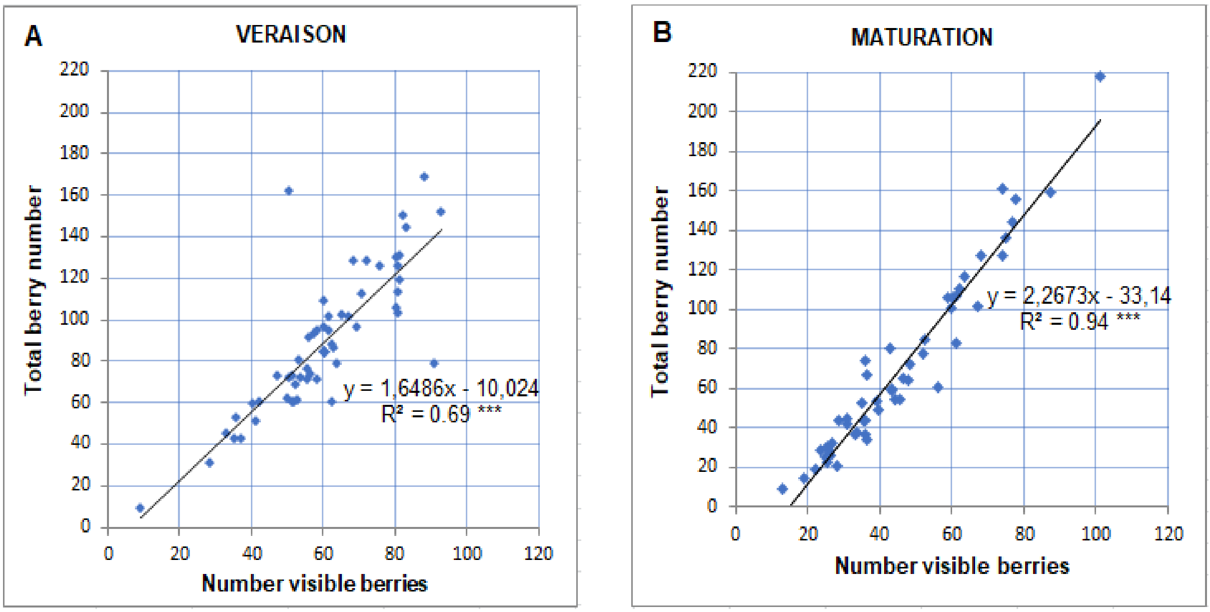

Figure 18. Relationship between number visible berries (independent variable) and total berry number (dependent variable) with respective linear regression equations and coefficient of determination (R^2) at veraison (A), and at maturation (B). The *** indicates the significant R^2 at p≤0.001.

5.1.4. Relationship between the average number of visible berries and bunch weight

At veraison the regression presented an R^2= 0.64 (Fig. 19A), while at maturation it was 0.91 (Fig. 19B). These significant coefficient of determination, indicate that the number of visible berries explains a very high percentage of bunch weight variability, especially at maturation.

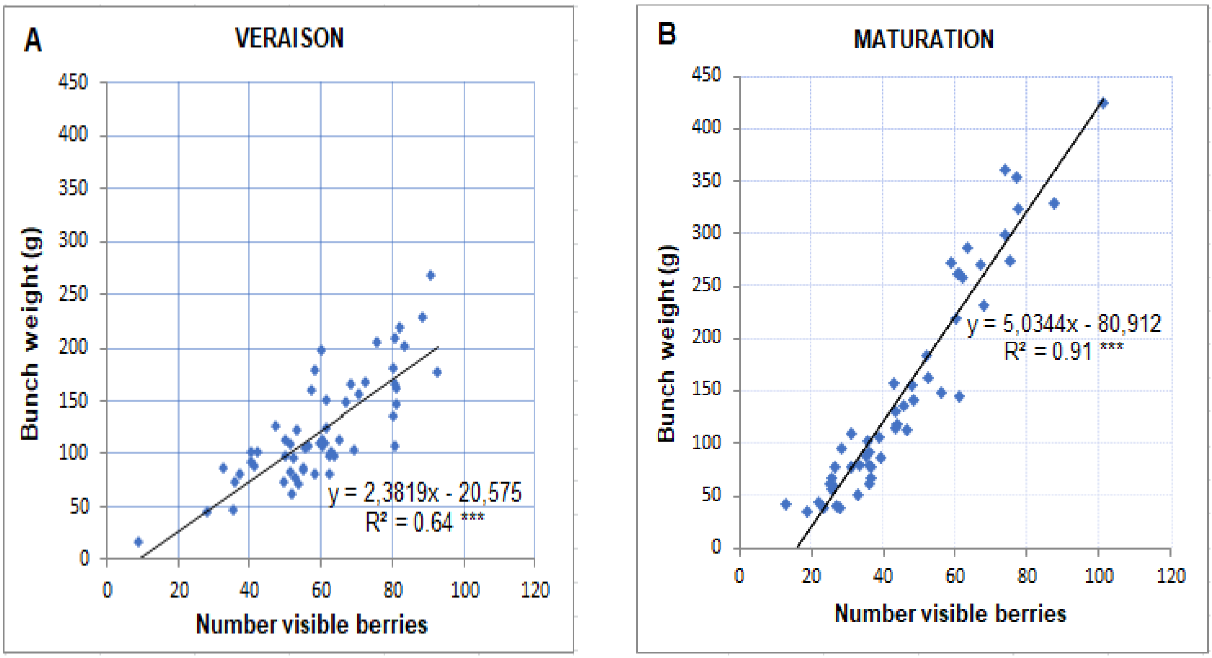

Figure 19. Relationship between number of visible berries (independent variable) and bunch weight (dependent variable) with respective linear regression equations and coefficient of determination (R^2) at veraison (A) and at maturation (B). The *** indicates the significant R^2 at $p \leq 0.001$.

5.2. Field manual images

Average VBA and the % of Vb_v in field conditions increased with the increase in the level of defoliation both at veraison and maturation, as was easily conceivable. 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 (table 3). These results confirm the thesis that if the porosity increases, the number of visible berries increases as well (Lopes et al., 2017).

Furthermore, at maturation, for all levels of defoliation, the Vb_v were in a higher percentage than those identified at veraison in vines with the same levels of defoliation, this is not due to the increase in the size of the berries in the time interval between the two phenological phases because looking at the VBA values at maturation and comparing them with those at veraison, these decrease in the non-defoliated vines or remain constant as in the case of partial and total defoliation.

Probably the slight increase in Vb_v (%) is caused by leaf senescence which grows from veraison to maturation. These results have already been identified by Victorino et al. (2020), which took into consideration the bunches instead of berries, in which a slight decrease at harvest is observed due to the average occlusion of the bunch by the leaves.

This phenomenon was noticed for all the varieties considered in the research but the Syrah variety featured a more evident difference. According to Victorino et al. (2020), this is attributable to the fact that the Syrah vineyard was not irrigated and therefore presented a greater water stress that led to an increase in leaf senescence. In our research, the experimental vineyard of Encruzado is irrigated and this could explain a lower leaf senescence, due to a lower water stress, consequently the slight increase in Vb_v (%).

Table 3. Average values (± standard deviation) of the % porosity (P), the visible bunch area (VBA) (estimated manually using the ImageJ software) and the % of visible berries at vine level (Vb_v) (estimated manually using the MATLAB software) on Encruzado vines with different degrees of defoliation during the phenological stages of veraison (n=45) and maturation (n=45).

Defoliation degree	VERAISON			MATURATION		
	P (%)	**VBA (cm^2)**	**Vb_v (%)**	**P (%)**	**VBA (cm^2)**	**Vb_v (%)**
No	7.7 ± 6.3	141 ± 76	23.6 ± 8.6	7.7 ± 3.8	127 ± 103	27.3 ± 8.9
Partial	15.1 ± 4.7	310 ± 106	54.7 ± 16.8	19.4 ± 7.3	311 ± 158	58.9 ± 20.1
Total	59 ± 9.5	623 ± 209	100	65 ± 6.6	618 ± 259	100

5.2.1. Correlation analysis

Porosity presented high and significantly positive r values with Vb_v, both at veraison and maturity.

Regarding the correlation between VBA and Vb_v, it presents very high and significantly positive values of r in both the two phenological phases, being the r very similar between the two phases.

In the works of Aquino et al. (2018); Nuske et al. (2014); Grimm et al. (2018); Zabawa et al. (2019), the number of berries was used on the projected area of the bunch.

According to Victorino et al. (2020), it is convenient to analyse the number of berries instead of the surface of the bunch due to their ease of being segmented in the image.

VBA is the average area measured on images taken from two perspectives. This is an optimistic approach as this result would hardly be obtained in field conditions. On the other hand, Vb_v, which is the number of visible berries in the vine, made this approach not optimistic because it does not consider the berries which cannot be visible.

In the future, both the area of the bunch and the number of berries could be considered together to explain the yield of the vine. Each variable would contribute individually, but would make the algorithms less dependent on changes in variety, related for example to the compactness of the bunch. In the future, an index capable of combining the visible berries and the visible area of the bunch into berries per unit area of the bunch could be an advantage for the robustness of the vine yield estimation algorithms.

The actual yield (Y) presents a significant positive r with the Vb_v both at veraison and at harvest. This means that, with or without defoliation, the visible berries already prospect, to some extent, the final yield on the image. However, the r values are not very high and to perform a yield estimation, further help from other variables would be required.

An interesting correlation value is given between Vb_v (%) and P with high and significantly positive values of r both at veraison and maturation, with a slightly higher r in this last phenological phase, probably due to the fact that Vb_v (%) increases at maturity because the size of the berries increase.

These variables with high and significantly positive r, if detected in the appropriate way, are useful 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 at vine level (Vb_v), % porosity (P), visible bunch area (VBA) and actual yield (Y).

	VERAISON					MATURATION				
	Vb_v	**P (%)**	**VBA**	**Vb_v (%)**	**Y**	**Vb_v**	**P (%)**	**VBA**	**Vb_v (%)**	**Y**
Vb_v	1					1				
P (%)	0.75^{***}	1				0.59^{***}	1			
VBA	0.98^{***}	0.77^{***}	1			0.96^{***}	0.66^{***}	1		
Vb_v (%)	0.81^{***}	0.88^{***}	0.82^{***}	1		0.67^{***}	0.91^{***}	0.73^{***}	1	
Y	0.38^{*}	-0.08^{ns}	0.38^{*}	-0.01^{ns}	1	0.58^{***}	-0.08^{ns}	0.47^{**}	-0.07^{ns}	1

* indicates significance at P ≤ 0.05, ** indicates significance at P ≤ 0.01, *** indicates significance at P ≤ 0.001. ns = not significant.

5.2.2. Models to estimate the berries covered by leaves

These polynomial regression models show an R^2 equal to 0.81 at veraison (Fig. 20A) and 0.88 at maturation (Fig. 20B). These are good values of R^2 and are also coherent with the data reported in the Table 4. Thanks to this polynomial model we were able to explain a higher fraction of Vb_v variability.

This regression analysis also shows coefficients of determination with high significance and, consequently, it is possible to use this model to estimate berries covered by leaves.

At harvest, we have a slightly higher R^2 compared to veraison, this may be due to the fact that P slightly grows due to leaf abscission and consequently the % of Vb_v grows as well compared to veraison.

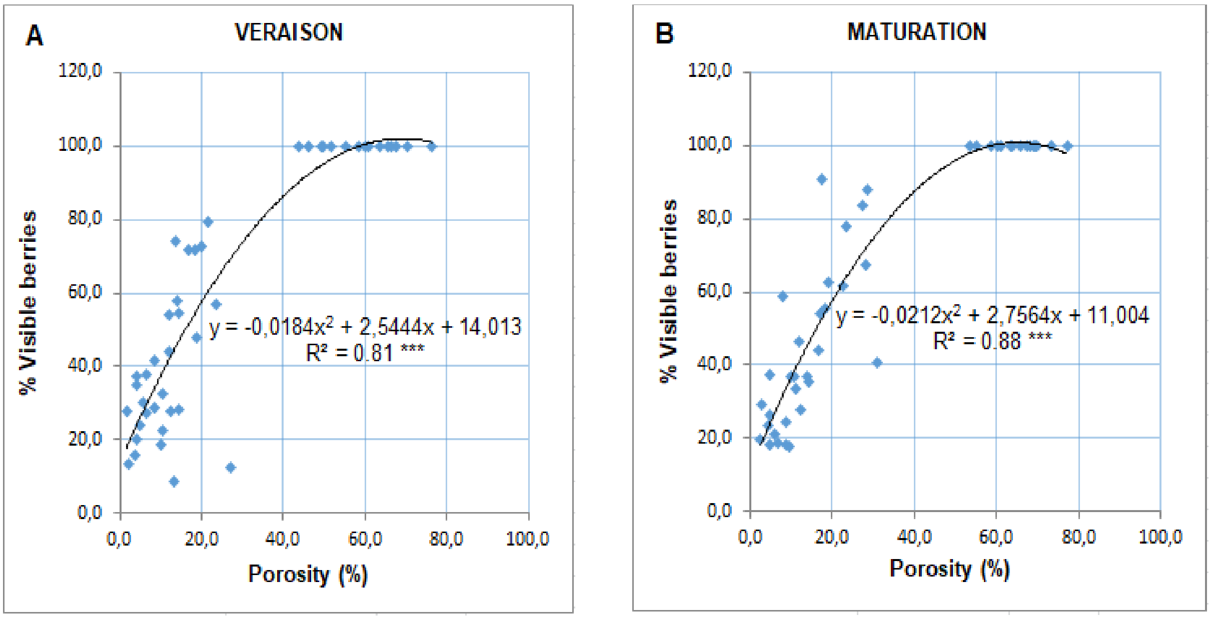

Figure 20. Relationship between the porosity (P) (independent variable) and the % of visible berries at vine level (Vb_v) (dependent variable) not covered by leaves with respective polynomial regression equations and coefficient of determination (R^2) at veraison (A) and at maturation (B). The *** indicates the significant R^2 at $p \leq 0.001$.

5.2.3. Relationship between the visible berry number and the actual yield

The linear regression models show a low and significant coefficients of determination for veraison (0.53) (Fig. 21A) and a high and significant coefficient for maturation, R^2=0.85 (Fig. 21B).

This difference in the R^2 values is not because of the occlusion of the berries from the leaves since these variables have been analyzed on vines with a total defoliation. As we have the occlusion of the berries by other berries, probably at maturation, we found a greater number of berries because in the time interval between the two phenological phases we had an increase in their size which made them more visible with image analysis.

Furthermore, at maturation, the R^2 is even more significant, therefore the Vb_v can be considered as an explanatory variable of the Y, particularly in this phase.

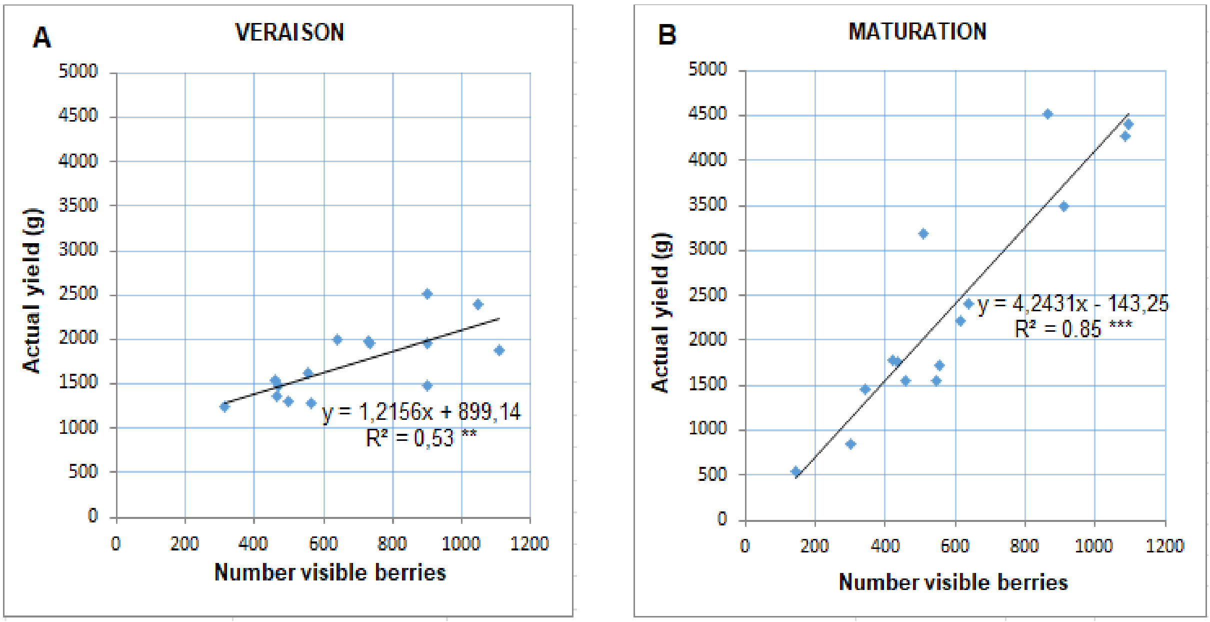

Figure 21. Relationship between the visible berries (independent variable) and the actual yield (dependent variable) with respective linear regression equations and coefficient of determination (R^2) at veraison (A) and at maturation (B). The ** indicates the significant R^2 at $p \leq 0.01$ and *** indicates the significant R^2 at $p \leq 0.001$.

5.3. Yield estimation with Vinbot

In these images more berries were identified on average at maturation than at veraison. This is not due to a higher % of P at maturation because this variable is higher at veraison, but it can be caused by the increase in the size of the berries at maturation. This is demonstrated, by a greater VBA at maturation, factor that make them more easily differentiated from vegetation (Table 5). These results are in accordance with Victorino et al. (2020) who states that on a fully developed canopy and without defoliation, the average visible area of the bunch increases from the pea size to veraison, probably because the area of the bunch has increased. This can also be assessed in laboratory conditions (Table 1), which showed increases in the BW, stating an increase in the VBA in field conditions.

At veraison, the higher % of canopy porosity (P) with respect to maturation, involves a greater % Vb, this is due to the presence of larger empty spaces in the canopy that make the berries more easily visible. In fact the % Vb are higher at veraison than at maturation.

Vbtot is directly proportional to Vb_v and inversely proportional to the % Vb, consequently we have an Vbtot greater at maturation, given the fact that in this phenological phase Vb_v was greater than at veraison.

btot is directly proportional to Vb_v, as one increases the other increases as a consequence. We can observe this trend also in the graphs of figure 18 of section 5.1.3. and in this case we have estimated a higher value at maturation in the light of the fact that Vb_v is higher at maturation and lower at veraison. The Yest is higher given that btot is higher at maturation as well.

Table 5. Summary statistics of measured and calculated variables in field conditions using the VINBOT platform and image analysis, at veraison (n=40 vine segments) and maturation (n=40 vine segments): number visible berries (Vb_v), % of porosity (P), visible bunch area (VBA), % of visible berries (% Vb), visible berries excluding occlusion from leaves (Vbtot), visible berries excluding occlusion from leaves and berries (btot), yield estimate (Yest).
Avg: average ± standard deviation; Max: maximum value; Min: minimum value.

	VERAISON			**MATURATION**		
	Min	**Avg**	**Max**	**Min**	**Avg**	**Max**
Vb_v	0	66.3 ± 40.8	160	0	72.6 ± 48.6	241
P (%)	1.4	6.9 ± 4.9	30.4	0.2	5.1 ± 4.7	30.4
VBA (cm^2)	0	100.2 ± 76.5	307.9	0	135.1 ± 89.4	388.4
% Vb	17.5	30.2 ± 10.1	74.4	11.6	24.1 ± 10.1	75.2
Vbtot	0	240.4 ± 160.4	656.4	0	326.3 ± 214.6	836.9
btot	0	386 ± 264.4	1072.1	0	706.7 ± 486.6	1864.3
Yest (kg/m)	0.1	0.8 ± 0.5	2.1	0.1	1.4 ± 1	3.7

Table 6 shows the Yest using VINBOT compared with the actual yield and the determination of the % of error which, in our case, is very high at veraison, while it decreases at maturation. Observing the data in Table 5 it is noted that the Vb_v and Btot at maturation are greater than at veraison, this has led to a higher Yest in this phenological phase.

Table 6. Determination of yield in field conditions by using VINBOT at veraison (n=40; vine segments) and at maturation (n=40 vine segments): estimate yield (Yest), actual yield (Y), % error (E).

Phenological phase	**Yest (kg/40 m)**	**Y (kg/40 m)**	**E (%)**
Veraison	31	69.3	-55.3
Maturation	56.7	69.3	-18.3

Figure 22 compares the yield estimate, determined by using the VINBOT platform, with the actual yield determined at harvest, showing the variation in yield.

As can be seen for both veraison and maturation, the estimated yield is lower than the actual yield, but it is possible to see that the trend of overestimation and that of underestimation are common. The trend of the lines are similar.

Regardless, there seems to be a common trend between the two curves, save for same specific situation like vine 11 or vine 33 (Fig.22 A).

At veraison, if all vine images are considered together, the final estimation of yield achieves 31 kg, 38.3 kg less than the actual yield (Fig.22 A), while at maturation, the final estimation of yield achieves 56.7 kg, 12.6 kg less than the actual yield (Fig.22 B).

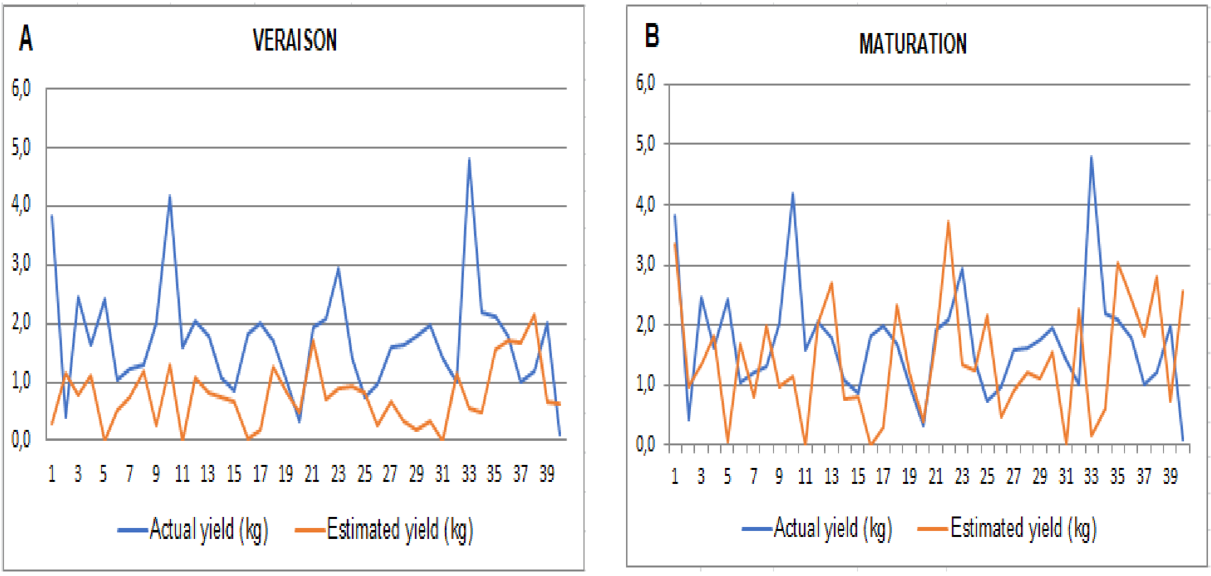

Figure 22. Comparison between estimated yield (kg) and actual yield (kg) at veraison (A) and maturation (B).

6. CONCLUSIONS

Through this thesis work we wanted to use the number of visible berries on bunch and canopy images to estimate the yield at two phenological phases (veraison and maturation) in an experimental vineyard with the white variety Encruzado.

With the data obtained in the laboratory, we have seen that there is a high correlation between the number of berries visible in the images 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 at maturation.

The regression analysis between the porosity of the canopy and the number of berries visible in the images showed high and significant determination coefficients, showing also that, at maturation, the visibility of the berries is more influenced by porosity of the canopy as compared to veraison.

With the regression analysis between visible berries and actual yield the R^2 were lower for veraison and higher at maturation, therefore we can conclude that the visible berry number is a good explanatory variable of the actual yield, in particular at maturation.

Lastly the yield of the vineyard at veraison and at maturation was estimated using the images captured by the VINBOT platform and was compared to the actual yield. We obtained an higher error at veraison as compared to maturation. In both estimations the errors are still high, in particular at veraison, which leads us to say that, in certain moments of the vegetative cycle, this method does not allow to observe a high number of berries which is attributable mainly to the occlusion by leaves, by other bunches, and by berries occluded by other berries within a bunch.

Based on the results obtained in this work, we can conclude that the use of visible berry number to estimate grapevine yield is a promising tool but still needs further work in order to achieve an accurate estimation.

One of the problems encountered during the analysis of Vinbot images with MATLAB, and which in the future needs a great improvement, concerns the distinction of the berries from the different vegetative components caused by low resolution photos taken by the RGB camera placed on the VINBOT platform. So to improve the yield estimate with Vinbot it would be a good idea to use a better resolution camera and maybe reduce the distance between the VINBOT and the vine.

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