A review of the issues, methods and perspectives for yield estimation, prediction and forecasting in viticulture

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Why is grapevine yield so challenging to report ?
A review of the issues, methods and perspectives for yield estimation, prediction and forecasting in viticulture.

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Abstract

Grapevine yield is defined as the quantity of harvest, expressed as either grape mass or wine volume units, which has been collected per surface unit and per crop cycle. The information about current and future yield, termed a yield report in this paper, is an essential decision-making element for the grape and wine industry. Crop management, wine-making, commercial, accounting and strategic operations are all adapted to and all impact on the expected yield of the current vintage. Numerous yield reporting approaches have been proposed in the scientific literature but only a few of them consider their adaptation to the operational context, which requires the constraints, needs and strategies of commercial vineyards and wineries to be taken into account. However, the few studies that have worked on the operational implementation of yield reporting methods have only partially addressed this issue, concentrating their improvement efforts on a single step in the yield reporting process. This paper therefore proposes to first review the characteristics of yield development in an operational context that must be taken into account by yield reporting methods : i) addressing the complex temporality of yield development, ii) ensuring a local monitoring of yield development and iii) fitting the operational needs to relevantly support decision-making in the field. The approaches of yield estimation, prediction and forecast are discussed in the way they address these challenges. In a second step, the paper proposes an understanding framework for the yield reporting process. It includes a review of the variables that are used to explain grapevine yield. Issues and proposals from the literature associated respectively with measurement, sampling and modelling yield are reviewed and the need for better modelling of relationships between explanatory variables and the desired, reported yield variable is discussed. The yield reporting methods found in the literature are categorised and compared according to measurement, estimation and modelling approaches, and then according to how the local, operational contexts influence the characteristics of yield development and the method of yield reporting, such that the report is adapted to commercial needs, and not to research objectives. In conclusion, concrete proposals for new grape yield reporting methods are discussed in order to investigate the as yet unexplored opportunities for improvement in yield reporting that have been identified in the paper. These considerations could easily be transposed to other perennial crops.

Keywords

Measurement, Sampling, Yield Models, Operational, Climate, Uncertainty

1. Introduction

For the wine industry, yield is agronomically defined as the quantity of harvest, either expressed in grape mass or wine volume units, that has been collected per surface unit and per crop cycle. Since the introduction of wine regulations at the beginning of the 20th century, grape and wine production has been seen as a trade-off between harvest quantity, i.e. yield, and quality (Ravaz, 1911 ; Champagnol, 1984 ; Guilpart, 2014). However, this trade-off is not bijective i.e. a given harvest quality does not imply a unique yield but can exist across a range of possible yields (Tardaguila et al., 2008 ; Intrigliolo and Castel, 2009 ; McClymont et al., 2012 ; Martinez et al., 2016). Therefore, grape yield can be optimised for a given harvest quality by applying appropriate technical operations throughout the production chain. To this end, decisions on operations, both in the vineyard and in the winery, are based on an expected final yield and expected growing conditions from the start of the season. Numerous approaches to report the expected final yield have been proposed in the scientific literature (Clingeleffer at el., 2001 ; Diago et al., 2012 ; Cunha et al., 2016 ; Nogueira et al., 2018 ; Sirsat et al., 2019 ; Zhu et al., 2020). In this paper, they are referred to as yield reporting methods when considered as a whole. Most of these studies are conducted in a context of research experiments aimed at statistically linking total yield to a yield component (Diago et al., 2012 ; Lopes et al., 2016 ; Cuhna et al., 2016), another plant-related variable (Cunha et al., 2010 ; González-Flor, 2014 ; Sun et al., 2017) or environmental variables (Nogueira et al., 2018 ; Sirsat et al., 2019 ; Zhu et al., 2020).

However, there are only a few studies that consider the adaptation of yield reporting approaches to the operational context of the production system. As a result, yield reporting methods are often adopted by the wine sector on the basis of scientific work although they have not necessarily been defined to be effective or even valid in such operational conditions. Indeed, the operational context includes additional needs and constraints to be met to ensure the smooth running of the production chain of any commercial vineyard/winery. The operational context also refers to data differing from those collected for a research experiment. Operational data is collected throughout the season for immediate decision-making purposes, e.g. weather data or field observations, but it is usually not intended to support any statistical analysis. The raised issue is hence about scientific studies accounting for operational needs, constraints and capabilities in terms of data acquisition in order to enable wine sector professionals to rigorously apply the methods proposed by literature in a production context.

Such a question is also of real interest from a scientific research perspective since adapting to production conditions requires reporting on a wide variety of grape yield development situations, which is likely to generate knowledge on this subject. In that respect, operational datasets often offer larger amounts of data, particularly in terms of time series, which can be used to improve yield modelling by supporting novel statistical approaches. However, the development of operational methods presents scientific challenges related to the quality, heterogeneity and low number of local, i.e. site specific, data to be taken into account. It is also dependent on the definition of indicators to be used, which in turn depends on the working habits of each enterprise. Finally, yield reporting methods constitute both a technical and social issue for the wine industry and it is the role of scientific research to address both. In particular, the development of more relevant reporting methods should encourage their adoption by the wine industry, promoting a virtuous approach to developing agri-services that collect data for their own improvement and to support further research studies.

The few studies that have adapted yield reporting to operational conditions have often focussed on improving only one step of the yield reporting process. For example, some studies have attempted to improve measurement issues by working on the automation of yield components counting (Aquino et al., 2015 and 2018 ; Liu et al., 2020) or total yield weighing (Tarara et al., 2014 ; Lopes et al., 2016). Others studies have sought to optimize sampling strategies (Araya-Alman et al., 2019 ; Oger et al., 2019). Although relevant, these studies remain limited in the way that they respond to operational issues since they aim to improve only one constitutive step of the yield reporting process. As a consequence, the yield reporting methods that are currently available to the industry have significant limitations, such as a high degree of imprecision and an inability to characterize the uncertainty associated with the yield reporting. Moreover, the extent of these limitations is difficult to quantify in regard to what can be reasonably expected under operational conditions since no single yield reporting approach has dealt with the problem in its entirety.

Any proposal for an operational yield reporting method can not be based solely on the optimisation of any single step of the yield reporting process. Instead, it must collectively assess issues associated with measurement and sampling approaches for both the estimation of explanatory variables and the estimation of the yield variable to be explained, as well as modelisation issues for the development of a yield reporting model. New methods will also require an analytical approach that considers the entire yield development process in relation to the operational needs and constraints resulting from the production context. However, there is no holistic synthesis of the existing literature on yield reporting methods to help to identify the key research and industry questions that remain to be addressed in order to achieve a robust, accurate method of yield reporting in commercial vineyards. To address this deficit, this paper first provides an overview of the yield development process under operational conditions and a summary of the subsequent operational needs and constraints related to yield reporting to finally identify the challenges to be accordingly addressed. Secondly, a knowledge framework of yield reporting methods is proposed. It is framed in terms of measurement, sampling and modelisation approaches for a yield reporting purpose. For each of these three topics, issues and literature propositions are presented. Finally, the methods proposed in the literature for yield reporting are reviewed with regard to their characteristics in terms of measurement, sampling and modelisation and to the challenges identified in the first part. In conclusion, concrete proposals for a new grape yield reporting method are discussed. These considerations are primarily aimed at the production of wine grapes, which constitutes the vast majority of published literature, but could easily be transposed to the production of table grapes, juice grapes or potentially to other perennial crops.

Definitions

Here are the definitions that support the discussion presented in this paper. They are listed according to the reading chronology of the paper.

GRAPE (ACTUAL) YIELD : quantity of harvest that is effectively reached, expressed in mass (kg or t) or volume units (L or hL) per plant or surface units (ha or a).

YIELD DEVELOPMENT CYCLE : overall process of grape or wine production, which includes different stages depending on the enterprise and target markets

YIELD COMPONENTS : grapevine reproductive anatomical structures that are successively settled during the vineyard part of a yield development cycle

VINEYARD : refers to both grapevine blocks and the company that cultivates it, as understood in vineyard estate

WINERY : refers to both the cellar in which the operations of wine-making take place and the company that actually produces wine and commercializes it. N.B.: sometimes the terms vineyard and winery refer to the same enterprise.

LOCAL: site-specific i.e. including effects of the environment (soil, climate, topography etc.), cultural practices, operational constraints, needs and strategies in particular the qualitative orientation of the production.

INPUT VARIABLE : a variable that influences yield development without being reciprocally influenced by yield development

MEASUREMENT : observation in the vineyard or in the winery, may be performed with or without the help of instrumentation

SAMPLING : choice of measurement sites (spatial sampling) and dates (temporal sampling) according to their representativity of a considered phenomenon

MODELISATION : establishing a statistical relationship between explanatory variables and a variable to be explained (here, grapevine yield).

YIELD REPORT : any kind of yield information, including yield estimation, prediction and forecast without distinction. Any yield reporting method involves : i) the estimation of explanatory variables and of the yield variable to be explained by means of a data collection (measurement and sampling methods), ii) the modelisation of the yield variable as a function of the explanatory variables.

YIELD ESTIMATE : assessment, based on data available at a given date, of a yield component or yield that is effectively reached at this same date and that cannot be exhaustively measured at the desired scale (temporal or spatial). The uncertainty accounted for by the estimate relates only to measurement and sampling issues and not to any future divergent evolution of the yield development process.

YIELD PREDICTION : assessment, based on data available at a given date, of a yield component or yield that will effectively be reached at a future date. Using estimates as explanatory variables and yield variable to be explained, it implies an additional modelisation approach. The uncertainty accounted for in the prediction interval refers only to the variability found in the training dataset.

YIELD FORECAST : assessment, based on data available at a given date, of a yield component or yield that will effectively be reached at a future date. The uncertainty accounted for in the forecast interval refers to the yield variability found in the training dataset and the natural variability of yield development that is never fully illustrated by the dataset.

2. Challenges of yield reporting methods in an operational context

2.1 Definition of grapevine yield development process in an operational context

Grape actual yield corresponds to the quantity of harvest that is reached in the field when limiting and reducing external influences have interfered with potential yield (Van Ittersum et al., 2013; Savary et al., 2018). External influences will be described in a further section of this paper. Grape actual yield, also called grape yield, is expressed in mass units per stock (Guilpart et al., 2014 ; Nogueira et al., 2018) or per area units (De la Fuente et al., 2015 ; Araya-Alman et al., 2019). It is the output of a yield development cycle, which is spread over at least two seasons before the harvest, starting in season *n*-1 and ending with the harvest in season *n* (Howell, 2001 ; Clingeleffer et al., 2001 ; Carmona et al., 2008 ; Vasconcelos et al., 2009 ; Guilpart et al., 2014). In an operational context, the definition of a yield development cycle often extends to harvesting and wine making operations e.g. the reproductive cycle does not only refer to the production of grapes but also of wine. From an operational perspective, external influences determining grape yield also transcend purely environmental factors to include cultural practices. The list of operations that are included in the operational yield development cycle and the subsequent yield units are therefore specific to each vineyard or winery. In particular, the yield range that can be elaborated in an operational context corresponds to a reduction in the range that would naturally have been possible without taking into account the production objectives (quality and yield) and the constraints of the winery. The operational actual yield could hence also be named marketable yield as suggested for vegetable crops by Viguier et al. (2018).

2.1.1 Description of an operational yield development cycle

Grapevine physiology is divided into vegetative development, characterized by one-season cycles, and reproductive development whose cycles last two seasons. At any given time, one vegetative cycle and two reproductive cycles are occurring simultaneously, leading to inter-cycle dependencies as a result of nutrient and water partitioning over the season (Petrie et al., 2000 ; Bates et al., 2002 ; Zapata et al. 2004 ; Zufferey et al., 2015 ; Zhu et al., 2018). Moreover, within each development cycle, a competition for nutrients and water is also observed between organs of the same plant, which are implemented either simultaneously or successively (Keller et al., 2010 ; Carrillo et al., 2015 ; Poni and Gatti, 2017). The yield development cycle process is therefore constantly integrating inter- and intra-cycle dependencies. Furthermore, in scientific literature, grapevine physiology is usually described at the organ or plant scale, whereas vineyard and winery operations are often managed at the block scale or larger. As the intent here is to present an operational yield development cycle that accounts for both vineyard and winery operations, the discussion will necessarily alternate between these two scales.

The grapevine yield development process is considered to start in the latent buds (Figure 1), which generally include three structures, or buds, that follow the same organizational pattern, but are in different states of progress (Pratt, 1971). Two of the structures, termed secondary buds, will only develop in season *n* if the primary bud is damaged (Vasconcelos et al., 2009). Within each of the three buds, a shoot apical meristem (SAM) first undergoes a phase of vegetative development and forms leaf primordia. Once three to five leaves have been produced, the SAM keeps growing in a succession of two nodes featuring a lateral meristem opposite a foliar primordium and a node that only features a foliar primordium (Pratt, 1971; Morrison, 1991). The lateral meristems are also called anlage or uncommitted primordium and may later result either in a tendril or an inflorescence. The physiological process of inflorescence induction is still being debated by scientists. It is defined as being the modification of gene expression that alters the balance of endogenous hormones in response to environmental stimuli (Boss et al., 2003 ; Vasconcelos et al., 2009

; Li-Mallet, 2017). Noyce (2019) suggests that the stimuli is not received by the leaves but by the SAM itself. The subsequent floral initiation is characterized by repeated branching, which promotes immature inflorescences. Depending on the experimental conditions, the floral initiation seems to occur approximately four to seven weeks after bud break in season *n-1* (Vasconcelos et al., 2009). Once there are one to four inflorescences established, the latent bud may enter into different levels of dormancy (Lavee and May, 1997 ; May 2004 ; Jones et al., 2009). Tourmeau et al. (1976) further suggested that some of the inflorescence primordia may also be implemented prior to the floral differentiation in season *n*.

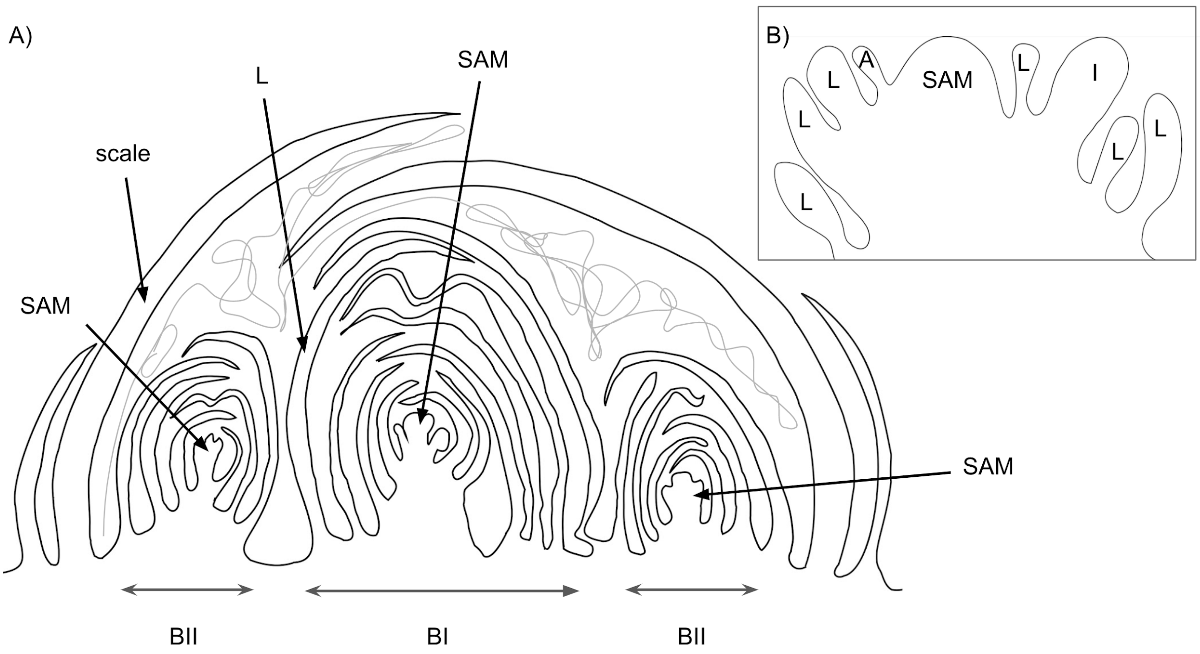

Figure 1: Outline of a longitudinal section of A) a grapevine latent bud (x10) and B) the upper zone of a grapevine primary bud (x100) with BI : primary bud, BII : secondary bud, SAM : shoot apical meristem, L : leaf primordium, I: inflorescence primordium, A : anlage

At the end of winter, only a portion of the latent buds are left after pruning. Shortly before and during the budbreak of season *n*, inflorescence primordia differentiate into flowers (Srinivasan and Mullins 1981 ; May, 2000 ; Vasconcelos et al., 2009). Inflorescence architecture has been described by May (2004) and Meneghetti et al. (2006). Self-pollination before the cap dehiscence is sometimes observed (Vasconcelos et al., 2009), although prevention mechanisms are implemented (Meneghetti et al., 2006). During flowering, cross-pollination by insects or wind has also been reported (Pratt, 1971). A few days are required for the completion of the pollination and fertilization stages that lead to the fruit set (Vasconcelos et al., 2009). Berries develop for approximately a hundred days after the flowering period in a double sigmoid pattern with two phases of active growth separated by a latency phase (Ollat et al., 2002 ; Bigard et al., 2019). After fertilization, the herbaceous phase corresponds to an accumulation of water (mainly via the xylem) and various assimilates, including malic and tartaric acids (via xylem and phloem), as well as to seed formation (Ollat et al., 2002). During this stage, operations of bunch thinning, foliar fertilization and irrigation may be undertaken using different strategies to promote berry development. Veraison is commonly detected by a change in berry colour but it seems to be more accurately approximated by the observation of berry softening (Bigard et al.; 2019). This stage marks the turn in berry metabolism. From then on, phloem unloading of sugars and polyphenols increases while xylem water supply is progressively stopped. During the ripening phase, sugar accumulation results in a second berry auxesis (Keller et al., 2015). Part of the malic acid is also metabolized (Ollat et al., 2002). The phloem flow then progressively stops and a decrease in berry volume may be observed due to dehydratation in relation with microclimatic conditions rather than plant water status. (Keller et al., 2015 ; Gambetta et al., 2020). This last stage is called the berry concentration phase and may last until the harvest is triggered.

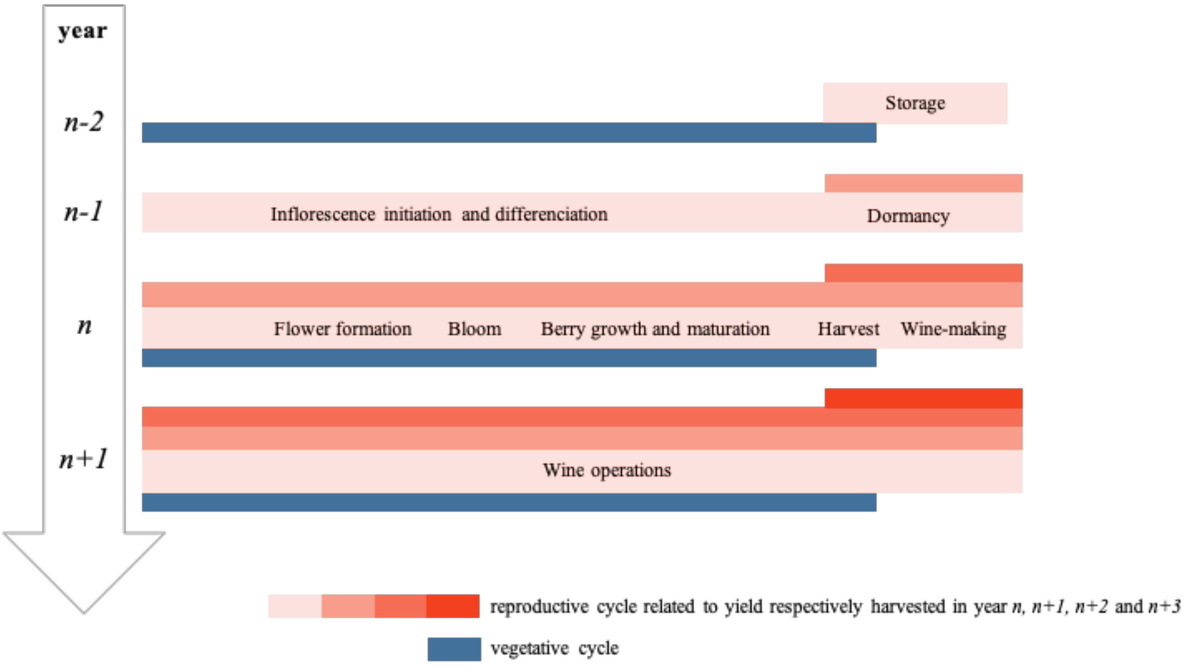

Figure 2 : Overlapping successive reproductive and vegetative cycles that compose grapevine physiology

2.1.2 Observable yield structures in the vineyard and the decomposition of yield estimation

Earlier stages of the yield development process occur in the bud at a cellular level and are not observable without specialised laboratory equipment. It is not until after bud break that producers can obtain a clear picture of yield potential. Since expected final yield in any given year is critical to within-season vineyard management, most of the successive reproductive structures, e.g. flowers, bunches and berries, expressed in the vineyard at the plant level are used as indicators of the vine's on-going reproductive development (Pagay and Collins, 2017). Table 1 shows a successive list of the main reproductive development stages post-bud break and the key indicators that could be measured at each stage. Counting these structures is often used to establish a percentage of the successful or deficient completion of the reproductive stages and an evolution in changes in expected final yield during the season. For example, the counting of flowers that turned into berries establishes the fruit-set rate. In some stages, counterpart phenomena, associated with a loss of yield, can also be observed and these are also indicated in Table 1. These yield loss phenomena can equally provide information on a changing expected final yield if correctly observed.

Table 1 : Most common vineyard yield indicators described in literature

Main reproductive development stage	Counter-part phenomenon	Indicators	References
Inflorescence induction	Bunch necrosis	Bud fertility (number of primary inflorescences per latent bud) Fertility index (number of inflorescences per cane) Number of inflorescences per vine stock	May, 2000 Collins et al., 2006 Guilpart et al., 2014
Inflorescence evocation			
Inflorescence differentiation			
Floral differentiation	-	Number of flowers per inflorescence	May, 2000 Gourieroux et al., 2016
Bloom Pollination Fertilization Fruit set	Millerandage Coulure	Pollen concentration Number of berries per bunch	May, 2000 Collins and Dry, 2009 Guilpart et al., 2014 Baby et al., 2015 Cunha et al., 2016
Berry growth	-	Berry mass	Dokoozlian and Kliewer, 1996 May, 2000 Guilpart et al., 2014

Few indicators tracing on-going yield development during the harvesting and winemaking operations are reported in literature. However, any estimate of the total yield may be considered as an indicator of the final total yield as expressed according to the winery practices. For example, the number of harvest baskets or containers may be an indicator of a final yield that would be captured after bottling.

The yield components in Table 1 are commonly associated within a formulae of the same type as Equation 1 to provide an estimate of grape yield in units of mass at the plant or block scale (Dry, 2000 ; Clingeleffer et al., 2001) by decomposing actual yield into its constituent components. Please note that some of the components of equation 1 are fixed (vines/field) while others are sequentially set during the reproductive cycle and will be dependent on effects in previous stages. As it relies on berry mass at harvest, Equation 1 is a theoretical equation that can only be fully derived retrospectively (post-harvest). Of course, growers and winemakers need information on yield potential in-season, not post-harvest, therefore historical averages or surrogate observations can be substituted into Equation 1 for early or mid-season estimations of yield. For example, the number inflorescences at bloom can be used instead of final bunch counts. The implications of the different timing of each yield component implementation are not considered in this section but are discussed further in the paper.

$$Actual\ grape\ yield\ (mass\ unit)\ = \frac{No.\ of\ Vines}{Field} \times \frac{No.\ of\ Buds}{Vine} \times \frac{No.of\ Bunches}{Bud} \times \frac{No.\ of\ Berries}{Bunch} \times\ berry\ mass\ (mass\ unit)$$

Equation (1)

In the literature, yield decomposition approaches, such as described in Equation 1, may be understood spatially, temporally or both. For instance, using a regularly distributed sampling design on an intra-field scale (nine vineyard blocks in one season), Carrillo et al., (2015) showed that the number of bunches per plant spatially explained 60% of mean field yield variability, while the number of berries per bunch, the berry mass and the interaction between the number of bunches per plant and the number of berries per bunch respectively explained 11%, 4% and 20% of the spatial yield variability. Clingeleffer et al. (2001) also reported that the number of bunches per vine explained 61% of the spatial yield variability along a 130 m long vineyard row in Australia. However, when separately studying several fields for 7 seasons, Clingeleffer et al. (2001) found that the role of bunches per vine was more variable when explaining temporal yield variability, explaining from 39% to 99% of the temporal yield variance. Guilpart et al. (2014) analysed several vine treatments for 3 seasons and reported that respectively 55%, 14% and 26% of the yield variability was explained by the mean number of bunches per vine, the mean number of berries per bunch and berry mass.

2.1.3 Overview of major factors influencing yield development

Operational yield is driven by internal plant factors (Boss et al., 2003 ; Carmona et al., 2008 ; Houel et al., 2015) as well as external factors that include environmental influences, interactions with neighbouring plants and cultural practices. Environmental influences are biotic or abiotic and are defined according to their nature, date of occurrence in relation to the grapevine development stage, duration and intensity. Abiotic environmental influences mainly refer to resource availability in relation to climatic conditions (e.g. temperature, light, rain, relative humidity and wind) and soil properties (Coipel et al., 2000 ; Van Leeuwen et al. 2018). Biotic environmental influences correspond to disease or pest development (Valdes-Gomez et al. 2008 ; Leroy et al., 2013 ; Guilpart et al., 2017 ; Ouadi et al., 2019). Inter-plant interactions may refer to intra-species interactions with neighbouring stocks or inter-species interactions with cover and inter-row crops or under-vine weeds. They are mainly described in terms of competition for light, water and nutrients (Champagnol, 1984 ; Garcia et al., 2018 ; Van Leeuwen et al., 2019). Cultural practices are relative to the vineyard's establishment i.e. vine density and spacings (Champagnol, 1984 ; Van Leeuwen et al., 2019), training system and canopy manipulation (Duchêne et al., 2003a and b ; Reynolds and Vanden Heuvel, 2009 ; Poni and Gatti, 2017) , pruning and fruit thinning (Naor et al., 2002 ; Keller et al., 2005 ; Reynolds and Vanden Heuvel, 2009), soil preparation (Ripoche et al., 2011 ; Guerra and Steenwerth, 2012), cover cropping (Celette and Gary., 2013 ; Garcia et al., 2018), fertilisation (Metay et al. 2015) and irrigation (Intrigliolo and Castel, 2009 ; Scholasch and Rienth, 2019). They may affect yield by modulating abiotic and biotic environmental factors as well as inter-vine competition.

The process of grapevine operational yield development is thus subject to numerous external influences and interactions. Effects of such interactions are difficult to identify and analyze separately. However, the most important from an operational perspective is to understand when the yield development process is influenced and the intensity of the influence. To this end, the problem is simplified in this section by considering only the factors initiating external complex influences. These input factors primarily influence yield development without any reciprocal influence. They are also identified as members of the active environment in the method for agrosystem conceptualization described in Lamanda et al. (2012). For example, weather variables are considered as input factors because they are not influenced back by yield development. In contrast, biotic aggressions are both influenced by climatic conditions and yield development. They are therefore not considered as input factors but as part of the studied yield development system.

By considering input factors, the goal of the next section is to determine the broad timeline for yield development. Each influence is described from literature results in terms of involved input factors, date of occurrence in relation to the grapevine development stage, duration and intensity.

Temperature

Temperature is mainly studied by computing the average, minimum and maximum of daily observations at a time scale from a day to several weeks (Guilpart et al., 2014 ; Gonzalez-Antivolo et al., 2018). Climatic indicators, for example focusing on heat accumulation or minimum temperature, may also be calculated in order to more specifically describe grapevine growing conditions (Tonietto and Carbonneau, 2004 ; Zapata et al., 2015 ; Badr et al., 2018). Both night and daytime temperature seem to play a significant role in determining yield development (Tombesi et al., 2018 ; Gaiotti and al., 2018).

Many studies have shown that the induction and initiation of undifferentiated primordia in season *n-1* requires high temperatures. The necessary minimum and sustained maximum temperature may differ from one variety to another with an optimum temperature for primordia formation seemingly around 25-28°C (Buttrose, 1974 ; Srinivasan and Mullins 1981 ; Dunn et Martin, 2000 ; Petrie and Clingeleffer, 2005 ; Vasconcelos et al., 2009). Zhu et al. (2020) suggested that daily maximum temperature around flowering in season *n-1* is the main driver of inflorescence initiation i.e. the number of bunches per vine. A short exposure of a few hours to high temperatures is sufficient to allow good bud fertility (Buttrose 1969b ; Srinivasan and Mullins, 1981).

Recent studies showed that the level of cold hardiness reached during the dormancy period between year *n*-1 and *n* is dependent on the plant material but also on the winter thermal history e.g. a vine subjected to warmer early and mid-winter conditions will be less resistant to cold events in late-winter or spring. However, the correct way to summarize the winter thermal history, e.g. via extreme or average temperature or by describing temperature trends over both short (days) and long (weeks, months) time steps is still an area being debated (Badulescu et Ernst, 2006 ; Ferguson et al., 2011 and 2014 ; Gonzalez Antivilo et al., 2018 ; Camargo-Alvarez et al., 2020).

During the period around bud break in season *n*, higher temperatures slightly increase the number of inflorescences per bud (Pouget, 1981), but reduce the number of flowers per inflorescence (Pouget, 1981 ; Dunn and Martin, 2000 ; Petrie and Clingeleffer, 2005, Jones et al, 2009 ; Keller et al., 2010). Higher temperatures may boost the growth of already formed organs to the detriment of flower differentiation or inhibit flower differentiation through enhanced production of cytokinines by already formed flowers (Pouget, 1981 ; Dunn and Martin, 2000 ; Petrie and Clingeleffer, 2005 ; Jones et al., 2009 ; Li-Mallet et al., 2016).

Temperatures favouring the largest number of flowers and flowers turned into berries are comprised in the range of 20 to 30°C for most varieties (Staudt 1982 ; Ebadi et al., 1996 ; Dokoozlian, 2000 ; May, 2000 ; Keller et al., 2010; Zhu et al., 2020). Optimal temperature for berry growth and maturation is between 25 and 30°C (Hale and Buttrose, 1974). A short but extreme heat event, i.e. superior to 35°C, applied at the pea size stage significantly decreased berry mass and repetitive heat events during berry growth may have cumulative effects on berry physiology and mass (Gouot et al., 2019b). Greer and Weston (2010) demonstrated that berry mass is more impacted by extreme heat events at veraison and mid-ripening than at fruitset.

Light

The main light characteristics that have been associated with grape yield development are intensity (radiation), quality and photoperiodism. Light intensity may have an indirect effect on all yield components through photosynthesis and assimilate availability, and a direct effect on buds by controlling gene expression or hormonal concentration (Vasconcelos et al., 2009 ; Li-Mallet, 2016 and 2017). Light intensity seems to be positively correlated to bud fertility when applied during the growth period of season *n-1* (Buttrose, 1969a ; Buttrose, 1970 ; Morgan et al., 1985 ; Sánchez and Dokoozlian, 2005 ; Zhu et al., 2020). Light requirements may differ according to grape varieties (Buttrose, 1970 ; Sánchez and Dokoozlian, 2005). Light intensity doesn't seem to influence the development of flowers during the bud break period of season *n* (Ebadi et al., 1996). In contrast, light deficit occurring during flowering of season *n* does induce a consequent decrease in fruit set and therefore in the number of berries per bunch in season *n* (Ebadi et al., 1996). Later, between fruit set and berry softening, a lack of light reduces both the size and mass of the berries (Dokoozlian and Kliewer, 1996) and this delay cannot be recovered even with a high luminosity applied during the maturation phase. This can be explained in part by a slowdown in the cell division and expansion rate (Dokoozlian and Kliewer, 1996). The effects of light quality (Morgan et al., 1985 ; Serat and Kulkani, 2013) and photoperiodism (Li-Mallet, 2016) on yield components have been little studied and remain unclear. Long continuous light periods seem to have more impact than shorter and alternate ones (Buttrose, 1970).

Water status

Water status is the difference between grapevine water absorption and transpiration. It conditions the implementation of most plant physiological processes (Champagnol, 1984). Both water deficit and excess are considered as water stresses, although the effects of a water deficit are most often studied. A persistent water deficit during season *n-1* seems to decrease both bud fertility and the number of berries per bunch by impacting inflorescence formation and the bunch necrosis rate during winter (Buttrose, 1974 ; Guilpart et al., 2014 ; Li-Mallet 2016). The period of highest sensitivity to water deficit in season *n-1* seems to happen after flowering (Guilpart et al., 2014). Similarly, persistent water deficit in season *n* appears to be detrimental to the number of berries and berry weight (Triolo et al., 2019). Rainy conditions prevent the dehiscence of the flower cap (May, 2004) or the pollen from being carried away by the wind (Cunha et al., 2003) and thus disrupts fertilization (Zhu et al., 2020). In contrast, low humidity conditions lead the stigma of the female flowers to dry out, preventing the pollen from adhering to it (Cunha et al., 2003). An early water deficit during the first period of berry growth is more detrimental than a late deficit because it irrevocably affects the auxesis processes and the resulting berry size (Matthews and Anderson, 1989 ; Ojeda et al., 2001 ; Scholasch and Rienth, 2019 ; Zhu et al., 2020). Roby and Matthews (2004) reported the existence of a threshold value of the midday leaf water potential involved in the inhibition of berry growth. Zhu et al. (2020) indicate that rain occuring around veraison of season *n* has a strong positive effect on berry mass at harvest.

Carbon and nitrogen nutrition

Leaf or bunch thinning operations aimed at modulating the leaf/fruit ratio show that both the number of inflorescences per plant (Vaillant-Gaveau et al., 2014) and the number of berries per inflorescence (Duchêne et al., 2003b) are impacted from the second year of treatment onwards. Reserve accumulation occurring in season *n-2* may therefore impact the yield in season *n*, probably by affecting the start of floral differentiation in season *n-1*. From flowering *n-1* onwards, the uptake of resources from the environment seems to be dominant and plant physiology becomes dependent on the nutrient supply (Lebon et al., 2008, Metay et al., 2015 ; Zufferey et al., 2015). Bud fertility, the number of flowers per inflorescence and the number of berries per bunch seem to be reduced by low nutrient status without the fruit set being impacted. Berry mass seems to be increased as a consequence (Duchêne et al., 2003a ; Bennett et al., 2005 ; Guilpart et al., 2014). Wood reserves and especially soluble sugars are correlated with cold hardiness of latent buds and therefore bunch necrosis. The nutrition dynamics of the reproductive development during season *n* seems to follow the same pattern as during season *n-1* but the effects of nutritional stresses on yield development are less pronounced (Guilpart et al., 2014 ; Bennett et al., 2005).

The results from the literature on the influence of input factors on yield components implementation have been synthetized into a timeline for yield development. This timeline is presented in Figure 3.

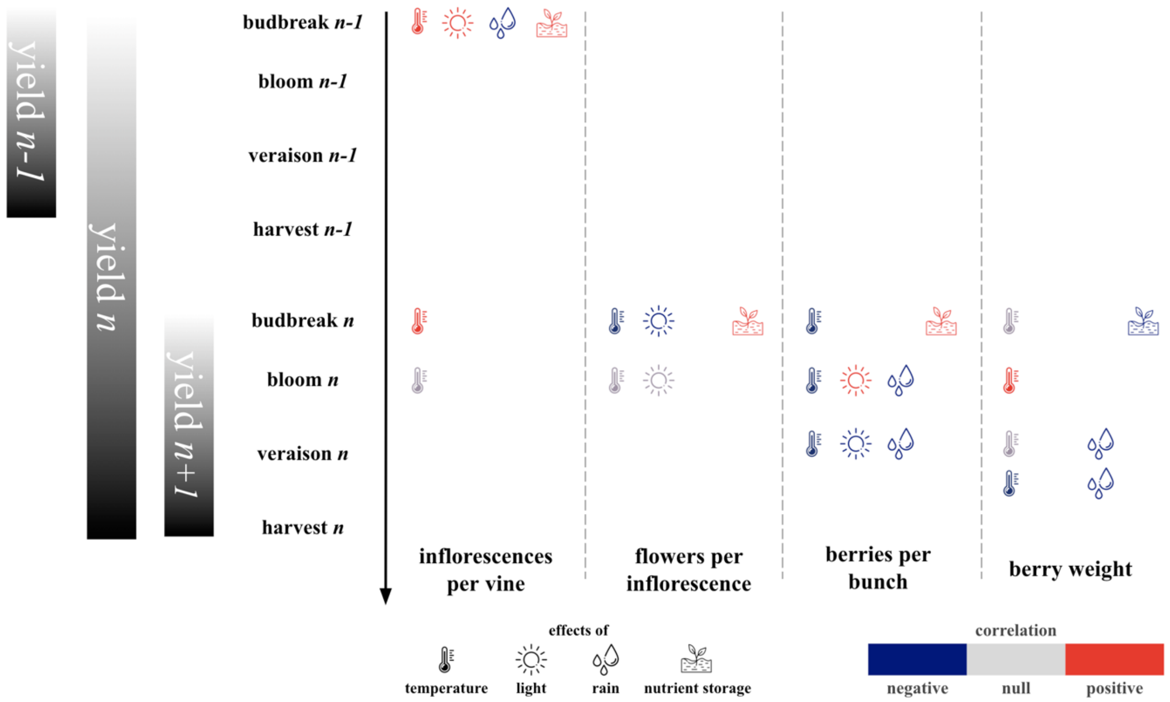

Figure 3 : Influences of temperature, light, water status and nutrition storage influence from season n-1 to n on yield components observed in season n that have been reviewed in literature. A null correlation means that the relationship has been shown to be absent by at least one study whereas empty cells mean that no study has been conducted on the considered influence.

2.2 Operational needs, constraints and challenges for yield reporting

2.2.1 Operational needs and constraints for yield reporting

Need for yield reporting with different characteristics depending on use cases

At the vineyard and winery scale, for each yield development cycle, a yield report is needed to support decision making associated with cultural practices, harvest, wine-making logistics, commercialisation and managing inputs and outputs for accounting. On a supply area or territorial scale, yield reporting is also an important decision-making support for trade purposes. On a longer term, yield reporting may be used for strategic purposes, either at the vineyard or winery scale or even larger (label area, supply area *etc.*). Table 2 summarizes the main expectations related to these different use cases. It is based on the consolidated interpretation of numerous conversations that the authors held in the field, in France and abroad.

Table 2 : Summary of the main uses cases for grape yield capturing (based on technical conversations) *The expected date, spatial scale and unit respectively refer to the date, the spatial scale and unit to report final yield that are desired by the industry. The associated operational decisions refer to the operations of the vineyard/winery whose decision is based on a yield report. The expected benefits refer to the reason for using a yield report to decide on such operations.*

Expected date	Expected spatial scale	Expected unit	Associated operational decisions	Expected benefits
before bud break of season *n*	field or within-field zones	mass per unit area	vineyards operations : reasoning pruning intensity and soil fertilization	optimized management of marketable yield
	wine blends	volume of wine blends after press	winery logistics : purchase of the barrels	costs saving, possibility to order any required material
during season *n*	block or within blocks zones	mass per unit area	vineyard operations : reasoning bunch thinning intensity, eventual fertilisation and irrigation level	optimized management of marketable yield
	one or several blocks	final volume of wine blends	accounting : managing stocks, planning revenue	good accounting, investment reasoning
	production area	final volume of wine blends	territorial agency : planning marketing and commercialisation wine traders : purchase contracting	profitable sales and purchases
just before harvest *n*	field or within-field zones in regards to all the fields to be harvested	mass per field	vineyards operations : organizing harvest, planning work force and allocating transport equipment	optimized harvest decision
	one or several blocks	mass per wine blend	winery logistics : making and allocating space in tanks, purchasing wine-making consumables, planning tasks and work force, scheduling harvest intakes and treatment	optimal harvest blending and gain in wine quality
	production area	wine final volume	territorial agency : announcement of an eventual regulation for harvest volumes	optimized commercialisation
longer term	production area	wine final volume	whole industry : anticipation of the effects of future contexts on wine production, market price etc. for research orientation and strategic development	business sustainability

Operational constraints and subsequent needs for yield reporting

If a yield reporting method respects operational requirements in terms of spatial scale, implementation date and yield unit, then its in-vineyard implementation depends on the operational criteria related to its ease of use. Concomitant workload and measurement time (including automation approaches) are considered reciprocally as a choice criterion: the higher the workload, the shorter the possible measurement time becomes and the more beneficial automation becomes. Easy to use equipment, as well as an easy protocol, will favour adoption. Cost also undeniably influences adoption but is rarely evaluated in scientific literature as equipment is seldom tested and designed under commercial conditions. Requirements for labour are also crucial, and access and cost of labour may vary considerably from one vineyard/winery to another.

Methods of determining yield components may be destructive or non-destructive. A destructive method may be adopted if its timing of implementation and/or the yield margin lost does not affect the yield goal. Therefore destructive methods are more likely to be used before crop load adjustment is made in a vineyard (e.g. shoot or bunch thinning). Advances, particularly in sensor technology, are changing the spatial density of observations and permitting the geolocalisation of these data. As a result, high resolution yield reporting is becoming possible (Taylor et al., 2019) to support spatial vine and crop management or differential, selective harvest.

2.2.2 Challenges to be addressed by yield reporting methods in an operational context

Temporality of yield development is complex

Yield development is a dynamic process punctuated by key steps that are dependent on the individual concerned and succession of the previous steps. The proportion of yield variability explained by each of these key steps varies depending on whether the decomposition of yield (cf. Eqn 1) is considered spatially or temporally and according to production conditions. Thus, the classical rule of thumb, according to which the number of bunches per vine, the number of berries per bunch and the mass of a berry respectively explain 60%, 30% and 10 % of yield variability, should not be taken as granted in any situation. Instead, it should be locally checked with a temporal, not spatial, analysis of yield variability if done for the purpose of yield reporting i.e. from year to year. The decomposition of yield variability varies because it depends on the external conditions of the vintage and on inter- and intra-reproductive cycle regulation mechanisms. The analysis of long time series data are therefore encouraged to better account for temporal correlations that may result in compensation and trajectory and even memory effects in the plant response to external influences (Duchêne et al., 2003 a end b ; Sadras et al., 2017 ; Vaillant-Gaveau et al., 2014 ; Guilpart et al., 2014 and 2017 ; Netzer et al., 2019). Successive operational needs in the vineyard and winery will require dynamic reporting to monitor yield development throughout the season. However, as Figure 2 shows, some yield components develop to a point where they become fixed and constant for the remainder of the season. Hence, there appears to be optimal periods during the growing season for capturing the best information on yield variability. Therefore, to optimise field observations and to consolidate yield report reliability, it would seem relevant to perform observations and yield modelling on a few key dates in the season. These dates will be driven by the grapevine phenology in a given season and will not be inter-annually fixed dates. To identify when these key dates are, or will, occur, yield components could be associated with variables that vary at an intra-seasonal time step, e.g. temperature data, and that are known to influence grapevine phenology and yield development.

Operational data are key to locally monitor yield development

As indicated in Table 1, operational yield development is a dynamic process that can be progressively described by observations of yield indicators. These indicators are only estimates as the measure is never exhaustive and final yield is dependent on berry mass at the time of harvest. The definition of final yield, and therefore the importance of the different yield indicators, varies from one vineyard/winery to another. For example, one vineyard may be in the habit of weighing harvest baskets directly in the vineyard while another winery estimates the volume of must after pressing or wine after fermentation. Moreover, environmental and managerial conditions that affect the yield development cycle are specific to each vineyard/winery, even each block, and to each year. Therefore, there is a real need for any form of yield reporting to use local data to capture the effects of local external influences on yield development as realistically as possible for each vineyard/winery.

In parallel, any yield report can be characterized by three criteria that summarize a typical use case : i) the definition of the reported final yield in relation to the stage of the production chain it is estimated at and the units it is expressed in, ii) the date at which the yield report is provided and iii) the spatial scale at which the yield report is provided. Please note that the date of yield reporting is necessarily concomitant or later than the production stage at which yield is assessed. According to the operational needs of the vineyard or winery, these three criteria may vary. For example, a yield report may refer to grape yield that will be reached just before harvest and therefore be expressed in mass units. This given yield report may be provided at the block scale and before bunch thinning i.e. before veraison. In contrast, another yield report may refer to bottled wine expressed in volume units. It may be provided at the whole production area scale just after harvest. A second interest of using local data is therefore to comply with the operational habits in terms of data collection and thus available indicators to monitor yield development.

From an operational point of view, such local data can only be collected by the vineyards or wineries themselves. The need to use local data to develop a more precise understanding of yield development raises issues of how to analyse these commercial, operational data. These data are characterized by a strong heterogeneity and parsimony in terms of the indicators available for analysis and for the implementation method. Moreover, these operational data inevitably contain noise (error) associated with data collection as well as errors on data traceability and management in the daily operational functioning of the vineyard/winery. Differential or variable management of operations that influence yield development in the vineyard and/or in the winery may vary, generating mismatches or overlaps that makes data traceability a real issue for a comprehensive analysis. For example, grapes from two blocks that underwent different bunch thinning may be picked together and then assembled in different proportions into two tanks, or a vineyard operation may be carried out imprecisely in time and/or space, which then causes a subsequent heterogeneous influence on yield development that is not captured, or is unable to be captured, in the yield report. A yield reporting method based on local data should permit an improved assessment of the inherent noise in these data. The sources of noise and error in these data will be explored later in the paper.

Yield reporting methods should comply with operational needs to support relevant decision-making

Grape yield development is a complex multifactor and dynamic process with numerous possible outcomes. This complexity can't be assessed with the same accuracy throughout the season since the development of reproductive organs is successive and some key components that determine the final yield (Eqn 1) are not determined until very late in the season (e.g. berry mass). Therefore, uncertainty regarding the temporal evolution of yield has to be handled by yield reporting methods in order to provide the user with sensible information for a sound, operational decision support system. The level and management of uncertainty for yield reporting will depend on whether the reporting is based on yield estimation, yield prediction or yield forecasting. A yield estimate is restricted to a temporary and immediate assessment of a quantity that cannot be exhaustively measured at the desired spatial or temporal scale. As illustrated in Figure 4, the uncertainty handled by a yield estimation is the irreducible noise that accompanies each attempt to estimate yield from the estimation of an explanatory variable. It is related to measurement and sampling errors (when collecting data) that can be reduced but never completely cancelled out. This is why, any observation in the field is always referred to as an estimate and not a real value. Moreover, a yield estimate is operationally interpreted to anticipate final yield. To do so, some human expertise is engaged to introduce a notion of uncertainty relating to the future outcome of yield development, which represents a poorly traceable and reproducible approach. As presented in Figure 4, the user expertise is engaged to expand from the technical uncertainty to be handled through the yield estimation process to the uncertainty that is required to be addressed when assessing yield future evolution. A more objective and reproducible way to do this is to use a prediction or a forecasting approach, that does take into account the uncertainty linked to the future evolution of a yield component or total yield. On one hand, a yield prediction quantifies this uncertainty on the basis of the available data. The uncertainty related to future yield development that is taken into account by a yield prediction therefore depends on the knowledge that has been developed through the collection of a historical dataset. On the other hand, a yield forecast also takes into account the uncertainty associated with the fact that yield development is a complex biological phenomenon whose possibilities are not fully contained in the historical dataset. As illustrated by Figure 4, the uncertainty handled by prediction methods is smaller and included in the uncertainty addressed by forecasting methods. Prediction methods are based on an example from a specific dataset of the natural uncertainty that is fully addressed by forecasting methods. In other words, both a yield prediction and a forecasting approach provide an assessment of the final yield in the form of an interval centered on a statistical expectation. However, the forecast interval may be broader and more fluctuating because it takes into account more sources of uncertainty, related to the natural variability of yield development, even in an operational context, and to any understanding that has been developed from the historical dataset (Wonnacott and Wonnacott, 1990 ; Saporta, 2011). Figure 4 illustrates the fact that forecasting methods address the widest level of uncertainty, including the uncertainty that is handled by prediction methods, which themselves include the sources of uncertainty associated with yield estimation methods or the estimation of any explanatory variable.

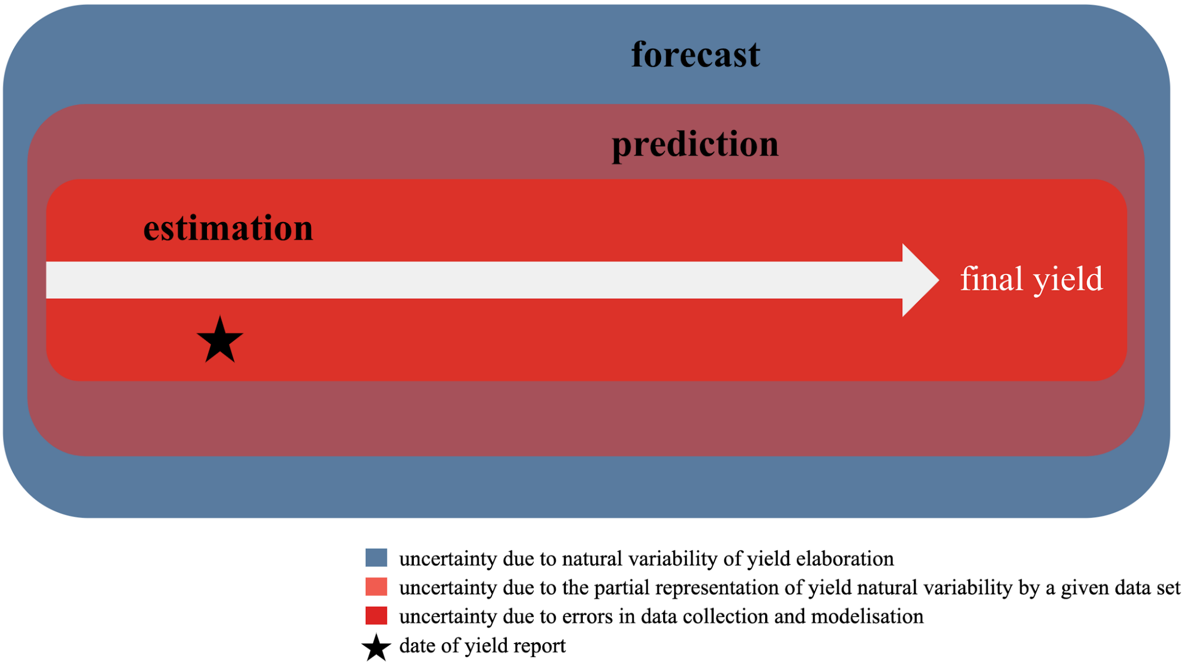

Figure 4 : Schematic illustrating the hierarchical nature of uncertainty associated with different approaches to yield reporting - estimation, prediction and forecasting. Uncertainty associated with more central approaches is intrinsically captured in more distal approaches.

Another issue that needs to be considered for the adoption of a yield reporting method in the field is the requirement that common operational constraints are taken into account in data collection. First and foremost, yield reporting methods need to be quick and easy to perform, as well as robust. In that sense, using a low number of variables (yield indicators) whose development and influence on final yield are well understood and modelled should be preferred. Measurement or modelling of input factors in the yield development system should be prioritised because their upstream influences on yield development are better understood both in terms of the conceptualization of the yield development process and in data analysis (Lamanda et al., 2012). Weather data and physical soil characteristics are particularly advantageous in this regard. SMART, i.e. Specific, Measurable, Attainable, Relevant and Time bound, indicators (Niemeijer et al., 2008) will encourage adoption, regardless of the yield reporting method, by providing ease of use and increasing operator trust by fostering robustness in the reporting. Finally, destructive field observations by their nature reduce any final yield potential and should be used sparingly and only for yield reporting at a few key dates during the growing season where the value of information gained is greater than the loss in yield potential.

3. Literature analysis on yield reporting methods

The previous section outlined the diversity of phenological stages in the reproductive process and the possibilities for external influences to impact on yield development in vineyards with very different operational contexts. This diversity of issues for yield reporting has resulted in a multiplication of methods that address different improvement objectives but which all need to be interfaced or integrated with each other and with the operational realities and challenges described earlier in the paper. Therefore, the focus of this section is to review the scientific literature on yield reporting in viticulture, identify strengths and limitations to current approaches and to develop and populate a framework to assist the development of future yield reporting methods. Some industry papers have been included in situations where commercial entities, and sometimes only a single entity, have addressed specific yield reporting issues.

3.1 A conceptual framework for yield reporting

The actual harvest yield can only be known if it is directly measured at harvest, and, as discussed in the previous section, this harvest yield is not always the marketable yield as there will be losses in the supply chain from the vineyard to the consumer (e.g. spoilage in table grapes or losses in the wine-making process for wine production). Yield reporting is needed to provide information on the expected yield (in the vineyard or to the consumer) to assist vineyard, winery and logistics management. Yield reporting is constrained by what can be observed and the relevance of the variables observed (measurement), how much data and/or how often the data can be obtained (sampling) and the models available to use these data (modelisation). To recall, data collection aims at building a dataset containing yield data as intended to be reported, *ie.* collected at the yield defining stage, yield data for training and other data collected for explanatory use. Modelisation aims at establishing a statistical relationship between training yield data and explanatory data. This conceptual framework is illustrated in Fig. 5.

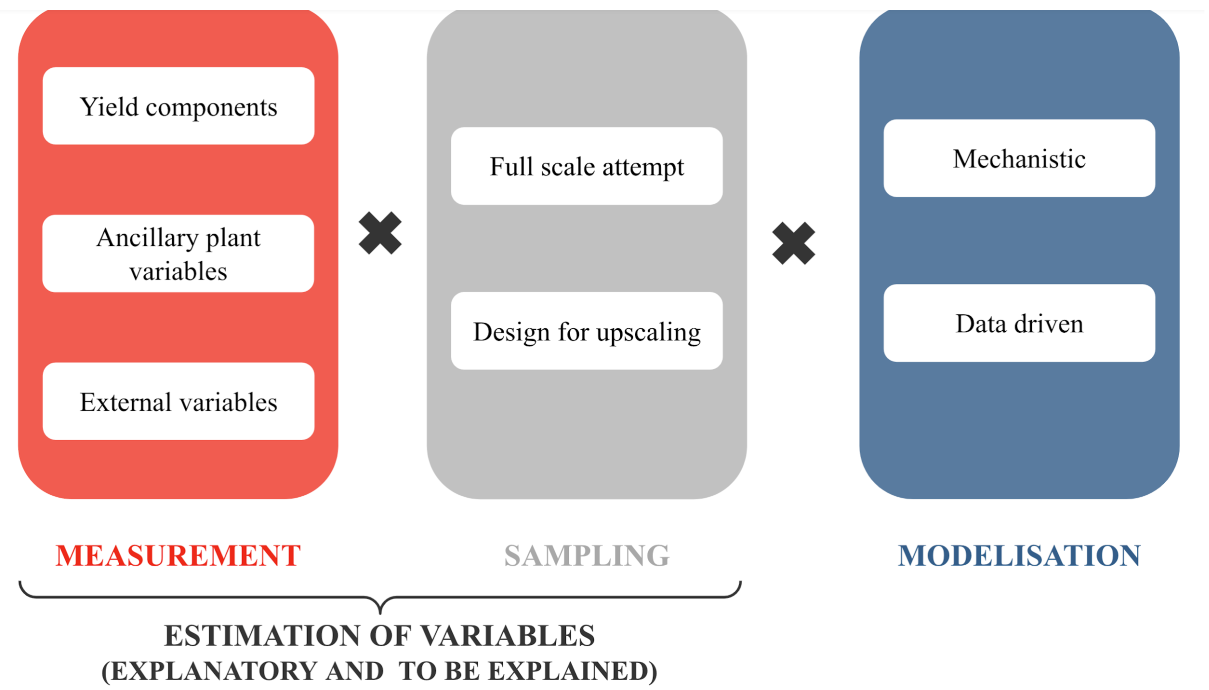

Figure 5 : A framework for constitutive steps of any yield reporting method

Collectively, the notion of Measurement and Sampling interact to generate an estimation of explanatory variables for yield reporting (Fig. 5). Explanatory variables may be yield components, ancillary plant variables associated with yield-determining processes (e.g. water status, canopy conditions etc.) or external factors (management or environmental effects) that have known or expected influences on the on-going yield development process. It is important to note that the yield components available will vary according to the characteristics of the intended yield report, particularly in regards to the timing and scale of the report. Consequently, these varying yield components will require adjustment of the theoretical yield decomposition equation (Equation 1). For example, if yield is aimed to be reported at the block scale, total yield per plant may be considered as a yield component, which is multiplied by the number of vines per block to report the total block yield. However, the total yield per vine may be measured directly (e.g. destructive harvest) or estimated through measurement of other yield components, such as the number of bunches per plant and bunch mass. Regardless of the explanatory variables to be observed, the quality of these data depends on the chosen measurement method and also on the method of sampling employed. Explanatory data may be measured exhaustively (full scale attempt) or estimated from punctual data (sampling design for upscaling) but remain estimates in any case. In the example previously, the total yield per vine was a full scale measurement of yield (at the vine-scale), while a decision on how many individual vines to measure would need to be made to allow a sufficiently accurate reporting of block yield (design for upscaling). Exhaustive (full scale) measurement has tended to be destructive in nature to date. However, imaging and sensing technologies are being developed at a rapid pace with the aim to observe the entirety of a yield component in the field (Sun et al., 2017 ; Millan et al., 2018 ; Ballesteros et al., 2020), although the complete measurement of yield components during the season (number of bunches, number of berries, berry mass, etc.) is not yet possible.

The final step in yield reporting is the modeliastion of the expected yield step (Fig. 5). Again, the model chosen will depend on the data and knowledge available as well as the objectives of the yield reporting. There are two main modelling strategies indicated (Fig 5) based on either :

i) using available scientific knowledge on yield development and on establishing an *a priori* mechanistic model. This may help to capture and understand the dominant mechanisms of yield development but it restricts the modelling to knowledge already discovered by previous work and may rely on generic, rather than local, interactions.

ii) using a data-driven approach in order to adapt the method to local schemes of yield development, which may lead to the detection of non-significant or erroneous relationships depending on the dataset and may not always be easily interpreted from an agronomic point of view. This is especially enhanced by new methods that use artificial intelligence.

3.2 Issues and methods associated with estimating the variables needed for yield reporting

3.2.1 Issues and methods for measurement of yield components

Issues for measurement are component specific

Issues with measurement differ between the different yield components. In chronological order, the first measurement of yield potential is gained through bud counts and bud dissection to determine the proportion of fertile buds and the number of potential bunches per bud. The number of fertile buds should preferably be assessed during a short period at the very end of winter when the final necrosis rate has been reached. Destruction is compulsory to observe bud content. The primordia dimensions are small and some of the undifferentiated inflorescences may not be detected or incorrectly counted. Following bud break, inflorescences are visible to the naked-eye in the developing shoots and can be more easily differentiated from canopy if counted early in the season (Wolpert and Vilas, 1992). As the canopy develops, identifying the inflorescence becomes more difficult. Bloom is a short phenological stage. Flowers are of small dimensions, high number and some of them may be hidden in the inflorescence architecture or whole inflorescences may be hidden in the rapidly developing canopy. The destruction of whole inflorescences for flower counting is often a sensitive issue for grape growers so early in the season as the risk of loss of inflorescences due to an external event is still high, and removing inflorescences reduces yield potential. Inflorescences become bunches, which are of a larger dimension, but may still be hidden in the canopy, which is continuing to develop and becoming more dense, depending on the trellis design and vine management (Nuske et al., 2014 ; Rose et al., 2016). While bunch number per vine and berries per bunch is fixed after fruit set, berry development is highly variable and the differentiation of verjuice, shoulder or deteriorated berries is not trivial in the field. Berries are numerous, relatively small and the more compact the bunch, the more hidden the berries may be. Moreover, still green or mature white berries are not easily distinguished from the canopy. Unripe berries are sometimes not counted according to the protocol adopted by a particular vineyard/winery. Mature berries may be damaged during handling, thus creating a difference between harvested yield and delivered yield. Additionally, berry dimensions change continuously during their growth and maturity, including the possibility for berry mass to decrease before the harvest due to dehydration. Table 3 summarizes from the authors knowledge the measuring issues to be considered for each yield component. The different difficulty levels should be considered as benchmarks that have been qualitatively settled from a consolidated interpretation of numerous conversations that the authors held in the field, in France and abroad.

Table 3: Operational issues for grape yield components measurement

+++ : very high difficulty, ++ : high difficulty, + : medium difficulty, empty cell : low difficulty (based on technical conversations).

Measured yield component	Short implementation	Small dimensions and mass	High number	Risk of visual obstruction	Risk of misinterpretation	Destruction requirement	Concomitant workload	Total difficulty
Inflorescences in the bud	+	++		+	++	+++		+++
Inflorescences post-budbreak			+	+				
Flowers	+++	++	+++	+++	+	++	+	+++
Bunches			+	++	+++		++	+
Berries	++	+	+++	+++	+	++	++	+++

Review of currently proposed approaches for yield components estimation

There are three methods of measuring yield components: counts, area and volume measures (sizing) and weights. Counting inflorescences, bunches and berries per vine(s) are the most common in-vineyard measurements. Sizing pre-harvest usually focuses on berry dimensions and berry mass to generate berry maturity curves to assist with yield reporting and with harvest logistics. Sizing post-harvest relates to volume measurements within pressing or wine-making processes. Weighing is used to generate actual yield mass, either by use of on-harvester yield monitors, weighting baskets/bins/gondolas in the field or truck weights on delivery to a grape crushing facility.

Measurements can be considered as either destructive or non-destructive and performed manually or using sensor technology. Destructive measurement implies a loss of grape production and therefore the number of pre-harvest destructive measurements performed is usually limited. Destructive sampling often requires the measurement to be performed quickly after removal or the yield component to be stored, e.g. frozen, for later analysis. Destructive sampling does allow measurements to be performed indoors in more controlled conditions and to overcome field difficulties posed by visual or handling obstructions, as well as changing environmental conditions. At-harvest or post-harvest, measurements are by definition destructive, but in-season vineyard measurements may be performed destructively or not.

Manual measuring is still commonly performed for in-vineyard or in-laboratory measurements. It often implies a limited investment in equipment and allows a better observation of occluded organs. However, manual measurements are prone to errors of concentration, perception and protocol interpretation as well as to the different capabilities and decisions of different operators (Carrillo et al., 2015). Moreover, manual measuring often involves time and labour costs, which constrains the number of measurements that can be performed. Given these limitations in manual sampling for yield reporting, there has been more research into the development of non-destructive yield component sensors in the past decade. This has been enabled by advances in computer science. The main sensing method is image analysis coupled to modern artificial intelligence (Aquino et al., 2015 and 2018a et b; Liu et al., 2018 ; Coviello et al., 2020). Image analysis has focussed on developing on-the-go automated sensing systems, often installed on vehicles for measurements (Lopes et al., 2016 ; Millan et al., 2018) and increasingly on unmanned aerial platforms (UAVs) (Di Gennaro et al., 2019) to generate high-resolution information on yield components. However, image sensors can also be deployed either in a laboratory, to speed up measurements, such as berry counts and berry dimensions, or manually in a field, typically as a low-cost mobile phone application to automate counting of yield components (Aquino et al. 2015; Aquino et al., 2018b). Manual picture taking is still subject to operator error but the prevalence of smartphone technology makes it very accessible. Different artificial intelligence algorithms allow yield component detection based on differences in colour, shape or texture (Nuske et al. 2014, Liu and Whitty, 2015 ; Pothen and Nuske, 2016 ; Abdelghafour et al., 2017 and 2019). Image analysis generally implies an increased repeatability and a reduced measurement time compared to traditional manual measurement, especially for components that are numerous, of small dimensions or of very short duration in the field. On-board image analysis methods aim to further improve measurement repeatability and reproducibility but are challenged by picture overlapping and geometrical referencing (Nuske et al., 2014). Image analysis requires the yield components to be completely visible and recognisable by artificial intelligence. For example, it cannot count berries on the reverse side of a bunch, nor can it see through leaves to count occluded bunches or berries. To circumvent this limitation, calibration methods to correct observed total yield in images have been proposed. Results have been positive but these have only been tested on limited datasets to date and their reproducibility is poorly evaluated (Nuske et al., 2014). When performed in the vineyard, methods based on image analysis are challenged by the varied shapes, dimensions and colour of grape yield components as well as a changing background and variable light conditions within the picture frame (Nuske et al., 2014 ; Grimm et al. 2019). Finally, the feasibility of in-vineyard imaging sensor systems is also dependent on the need to correctly deploy and to maintain the system.

It should also be noted that some direct mass measurements in-season within vineyards are possible, although not always commercially relevant. Commercial yield monitoring systems on grape harvesters have been demonstrated as a possible method of destructive yield estimation in mid-season in juice grapes (Taylor et al. 2016 ; Bates et al., 2018) as well as for yield-mapping at harvest. Alternatively, measuring the change in wire tension in single high-wire trellis systems (Blom and Tarara, 2009 ; Tarara et al., 2014) has been proposed as the only dynamic method to follow crop development via changes in mass, but it requires a permanent infrastructure that is likely cost-prohibitive outside of research activities.

Table 4 presents the main methods established for yield component measurement. Most of them are mainly used for research so far. Some of them also provide an estimation or forecasting method of grape yield, alike methods that directly link pixel detection to yield conclusions (Dunn and Martin, 2004 ; Diago et al., 2015).

Table 4 : Methods for yield components measurement reviewed in literature

Type of measure		Type of technology		Yield component measured	Date of measurement	Experimental dataset	Announced results	Rreferences
Count	destructive	image analysis in laboratory		flowers	bloom	3 inflorescence development stages 4 varieties 533 images	percentage error of 15.7% on validation dataset	Liu et al., 2018
				berries	just prior to harvest	10 varieties 100 bunches	r^2=0.71 on calibration dataset	Ivorra et al., 2015
					just prior to harvest	7 varieties 10 bunches per variety	r^2=0.62 to 0.95on calibration dataset	Diago et al., 2015
		manual		bud fertility	before budbreak	3 blocks 1 variety	no reference data	Rawnsley and Collins, 2005
				flowers	bloom	no published data	no published data	commonly used on field
				berries	after veraison up to just prior to harvest	no published data	no published data	commonly used on field
	non-destructive	image analysis in field	manually taken pictures	flowers	bloom	11 varieties 2 devices 140 images	recall from 0,80 to 0.91	vitisFlowers® Aquino et al., 2015a
				berries	from bloom to veraison	1 device 150 images	r^2= 0.92 between observed and simulated data	Grossetête et al., 2012
						8 varieties multiple devices 145 images	mean absolute error of 0.85% to 11.73% on calibration dataset	Coviello et al., 2020
						2 varieties 529 images	r^2= 0.88 to 0.95 on calibration dataset	Liu et al., 2020
					pea-size stage to bunch closing	12 varieties 2 devices	recall from 0.96 to 0.98	vitisBerry® Aquino et al. 2018b
			on-board	flowers	bloom	6 varieties 16 vines per variety 1 device	recall from 0.84 to 0.89 on validation data set	Palacios et al., 2020
				bunches	unknown	1 variety 5 meters of wire 2 treillis systems	recall of 77 and 82%	Rose et al. 2016
					harvest	respectively 190 and 35 images of white and red wines	respectively 91% and 97% of images with correct count	Reis et al., 2012
				berries	around veraison	3 varieties 229 plants 1 devices	undetected berries from 53.9 to 73.9 % of the total count	Nuske et al., 2011 Grocholsky et al., 2011
					from fruitset to harvest	6 varieties 1 device 1212 images	recall from 0.12 to 0.96	Nuske et al., 2014

					before and after thinning, just prior to harvest	3 dates 3 varieties (2019) and 2 training systems (2020) 60 images (2019) or 38 images (2020)	from 85.3 to 93.9% of total berries correctly detected (2019) and r^2= 0.972 to 0.988 on calibration dataset	Zabawa et al., 2020
					unknown	1 variety 10 bunches	recall of 77.2 and 77.6%	Rose et al. 2016
		manual		inflorescences	around bloom	no published data	no published data	commonly used on field
				bunches	after bloom and before veraison	no published data	no published data	commonly used on field
Size	destructive	image analysis in laboratory		bunches	just prior to harvest	10 varieties 100 bunches	r^2=0.82on calibration model	Ivorra et al., 2015
				berries			r^2=0.83 on calibration dataset	
				berries	prior to harvest	no published data	no published data	Dyostem®
		manual		berries	just prior to harvest	no published data	no published data	commonly used in field
	non-destructive	image analysis in field	manually taken pictures	berries	pea-size stage, veraison, harvest	3 varieties 3 phenological stages 750 berries per phenological stage	r^2=0.88 between observed and simulated data	Roscher et al. 2014
			on-board (but manually moved)	bunches	at harvest	49 bunches, 1 device	average absolute error of 67% on calibration dataset	Kurtser et al., 2020
Weight	destructive	manual		bunches	just prior to harvest	no published data	no published data	commonly used in field
				berries	just prior to harvest	no published data	no published data	commonly used in field
		image analysis in laboratory		bunches	just prior to harvest	7 varieties 10 bunches per variety	r^2= 0.65 to 0.97 on calibration dataset	Diago et al., 2015
				berries	just prior to harvest	7 varieties 10 bunches per variety	r^2=0.84 between observed and simulated data	Diago et al., 2015
	non-destructive	image analysis in field	manually taken pictures	bunches	fruitset, bunch closing and veraison	6 seasons, 4 varieties 50 to 200 bunches per varieties	prediction error from 6 to 15% on validation dataset	Serrano et al., 2005
			on-board	bunches	after veraison	1 season 1 block 1 row of 30 contiguous plants	r^2= 0.80 between observed and simulated data	Lopes et al., 2016 VINBOT®
		wire tension		total yield	dynamic	3 seasons 2 blocks 2 installations of 3 consecutive rows per block	r^2=0.84 to 0.98 on calibration dataset	Blom and Tarara, 2009 Tarara et al., 2014

3.2.2 Issues and methods for measurement of ancillary plant variables and external factors

The ancillary plant variables associated with grape yield reporting are mainly related to vine water status, nutrient status and canopy conditions. In this section, only an overview of the numerous and diverse measurement methods is provided for each type of variable, with an emphasis on methods that are used in operational vineyard situations (not just in research). Specific references are given for more details in Table 5.

In any case, it is important to note that plant water and nutritional status as well as canopy conditions are complex parameters that can be addressed in many different ways. The choice of the parameter that is measured and the element or plant organ on which the measurement is made is therefore very influential on the yield reporting process. The methods are also very different in terms of cost, ease of implementation and temporal and spatial support of implementation (punctual or continuous). This often involves a trade-off between the information desired and the methods implemented. Depending on methods available and local operational expertise, more expertise and additional parameters may be required for a good interpretation in the context of yield reporting.

In the field, plant water status may be estimated by direct observation. Methods such as the Shoot Tip Index (Rodriguez Lovelle et al., 2009) have been developed to guide visual assessment (Brunel et al., 2019). Grapevine water status may also be indirectly and roughly estimated through soil moisture measurement, especially with tensiometric measurements (Dobriyal et al., 2012 ; Rienth and Scholasch, 2019). Tensiometers are economical and relatively easy to use sensors that can be used all year long, including in winter to assess the soil water recharge. Tensiometric measurements are therefore largely deployed in the field. However, the reference method to measure plant water status still remains the leaf water potential measurement using a pressure chamber. Measurements in the pressure chamber are supposed to directly represent the water conditions experienced by the plant at a certain punctual time. However, the stability of the balance between the potential measured on the petioles and the water potential of the rest of the plant is debated (Rienth and Scholasch, 2019). Pressure chambers are more expensive than tensiometers and their use requires a demanding protocol, particularly in terms of timing (cf. predawn, midday or stem water potential) and the time needed for a single observation. This permits only a few measurements to be performed per day. Continuous measurements are possible using sap flow technologies, but this also corresponds to more expensive semi-permanent installations (installed for a season). Other methods exist to directly measure plant water status but are mainly used for research purposes (Santesteban et al., 2015 ; Lavoie-Lamoureux et al., 2017).

Grapevine nutritional status is either estimated during winter by measuring wood biomass (usually number and diameter of shoots) or during the season thanks to petiole laboratory analysis or via an optical measurement of Nitrogen content. Wood biomass gives an indication about the amount of carbohydrate reserves (Demestihas et al., 2018). It is also used to measure vine crop load with the Ravaz Index (Champagnol, 1984). Wood biomass is measured manually or thanks to on-board equipment (e.g. Physiocap® sensor, E.RE.C.A). Laboratory analysis of petioles provides detailed information on the concentration of nitrogen and other minerals, especially potassium (Cozzolino et al., 2020). However, they are destructive methods that require a demanding protocol to be performed quickly. Leaf nitrogen content can be estimated using chlorophyll fluorescence sensing (Cerovic et al. 2015), which can be performed manually and non-destructively in the field. Canopy dimensions are still mostly evaluated by manual measurement but remote sensing is becoming more common, with new companies entering the market. Remote sensing is primarily used to identify areas of differing vigour in vineyards. There is a shift toward using proximal and remote sensing for biophysical vine parameters but this is still mostly research-oriented. Remote sensing can be performed manually (pedestrian transport) or on-board a terrestrial vehicle, air-borne vehicle (UAV, plane) or satellite. Remote sensing performed on land (pedestrian transport or with terrestrial vehicles) may also be called proximal sensing in some publications. The characteristics of these remote sensing methods are very different depending on the signal characteristics (active or passive, wave length etc.), the need for correction of the raw signal and the spatial and temporal resolution of the captured images (Weiss et al., 2020 ; Gautam et al., 2020). Based on these characteristics, numerous vegetation indices have been proposed to serve different operational applications.

Table 5 : Main methods for plant ancillary variables measurement in commercial vineyards

Plant ancillary data		Type of measure		Type of technology	Temporal support	Spatial support	References
water status	soil	non-destructive	mass water content	gravimetric method	punctual	punctual	Rienth and Scholasch, 2019 Dobriyal et al., 2012
			volumetric soil moisture content	- neutron probe - time domain reflectometry - capacitance - gamma ray attenuation - ground penetrating radar	punctual or continuous	punctual	
			water potential	tensiometer pressure plate method	punctual or continuous	punctual	
	atmosphere	non-destructive	evapotranspiration	weather sensors	continuous	punctual or continuous	Rienth and Scholasch, 2019
	water balance	non-destructive	total or fraction of transpirable soil water computation	weather sensors, soil granulometric analysis, root depth measurement	continuous	punctual or continuous	Rienth and Scholasch, 2019
	plant	destructive	carbon isotope discrimination	mass spectrometry	punctual	punctual	Brunel et al., 2020 Rienth and Scholasch, 2019 Lavoie-Lamoureux et al., 2017 Santesteban et al., 2015 Herrero-Langreo et al., 2013
			water potential	pressure chamber	punctual	punctual	
		non-destructive	visual observation	field observation, apex method	punctual	punctual	
			stomatal conductance and leaf gas exchange	porometer or infrared gas analyzer	punctual	punctual	
			sap flow	stem heat balance	continuous	punctual	
nutrition and storage	wood	non-destructive	shoot number and diameter	manual	punctual	punctual	Champagnol, 1984
				laser image analysis	punctual	continuous	Demestihas et al., 2018 Physiocap®
	leave and petiole	destructive	nitrogen and minerals content	laboratory analysis including near infra-red spectroscopy	punctual	punctual	Cozzolino et al., 2020 Cerovic and al., 2015
		non-destructive	chlorophyll content	transmittance sensing	punctual	punctual	

	fruit and must	destructive	nitrogen and minerals content	laboratory analysis including near infra-red spectroscopy	punctual	punctual	
canopy	height, leaf area, porosity	non-destructive	sizing	manual	punctual	punctual	Weiss et al., 2020 Gautam et al., 2020
			passive reflectance	visible or RGB image analysis	punctual	continuous	
			active reflectance	visible, laser or multispectral image analysis	punctual	continuous	
	vegetation indices	non-destructive	active reflectance	RGB, multispectral and thermal image analysis	punctual	punctual or continuous	
			passive reflectance	RGB, multispectral and thermal image analysis	punctual or continuous	continuous	

Weather data is the other main external variable to be measured in vineyards. This is often done using fixed weather stations (either on-farm or from a nearby reference point) together with some form of extrapolation from the weather station position to the vineyard. Weather stations for agriculture are well developed and temperature, rainfall, relative humidity, wind and global radiation information can be routinely obtained at very high temporal resolutions. The authors have chosen not to venture into a description of weather sensors here although it is important to note that the appearance of virtual weather stations, through weather modelisation, has opened up a new and easier access to local weather data for producers beyond having fixed weather stations.

3.2.3 Issues and methods associated with sampling for yield reporting

Grapevine yield has been shown to be highly variable, both temporally at the block-scale (Chloupek et al., 2004; Clingeleffer et al., 2001) and spatially at a within-block scale in a variety of different production systems (Taylor et al., 2005). To achieve a representative yield value from point measurements, the number of measurements needs to reflect the expected variance in the system. However, yield related data measurement represents a significant effort in terms of labour and cost, logistical organisation and increasingly in equipment and technology costs. It is often an arduous task that is usually required (and performed) at periods during the season when concomitant workload is high. Thus, there is an optimisation function to be solved between the value of the yield report, the cost of the effort required to obtain the report and the offset cost of not performing other concomitant vineyard activities. While this optimisation function has not been formally defined or solved to our knowledge, sampling designs are a first answer for yield reporting at a seasonal or block scale under commercial operating conditions. A sampling design corresponds to a reasoned number, timing and location of measurements aimed at estimating yield components or total yield that is operationally acceptable in terms of precision and effort required. It is important to note that each grower is likely to have a differing idea of the level of precision required and the affordable effort available, although to date, proposed sampling designs for grape yield reporting have not considered this constraint. Issues and constraints in grape yield sampling that have been addressed in the literature are reviewed in the following sections.

Issues related to the selection of representative sites

The collection of yield component data is more relevant during key phenological periods when components of the final yield potential (Eqn 1) become fixed (Wolpert and Vilas, 1992). The optimal timing of measurements can be determined by considering the date when a yield component is no longer evolving. However, it may not be easy to identify these key dates in the field, especially when they occur asynchronously in space and time (Verdugo-Vasquez et al., 2020). This is further complicated by a lack of consolidation in the literature on the method of reporting of timings. Some studies have reported the timing of their observations in terms of calendar days from the completion of a commonly observed phenological stage e.g. bud break, bloom, fruitset, veraison (Petrie and Clingeleffer, 2005 ; Molitor and Keller, 2017). The start and end of these stages are open to different interpretations in different years and in different regions or locales. The use of a fixed day time step also ignores local environmental effects, particularly thermal time effects, on vine and berry development. This limits any global comparison or the derivation of general conclusions on the timing of reproductive development in vineyards outside the studied and reported areas. This shows the necessity to work with a time expression that captures the reproductive development conditions being experienced by the vine.

Within the field, environmental influences may generate random or structured spatial patterns that may or may not be temporally stable (Clingeleffer et al., 2001 ; Tisseyre et al., 2008). Therefore, every berry, bunch, vine and zone within a block or a vineyard can be considered as experiencing a different combination of environmental conditions that are rarely measured. Furthermore, as grapevine physiology and development is subject to fixed acrotony rules under spatially heterogeneous environmental influences, phenological asynchronicity is expected at all scales, from berries within a bunch (Bigard et al., 2019) to zones within a field (Verdugo-Vasquez et al., 2015, 2017 and 2020). This phenological asynchronicity also implies that every berry, vine or every block will not respond in the same way to these external influences, which in themselves will vary spatially. Correctly sampling under these conditions implies the selection and location of samples that are able to represent population distributions in the area to be studied i.e. in the geographic space, for example by using a grid design, and/or across the known variability in yield components i.e. in the attribute space. It is therefore preferable to avoid measurements associated with rare events or abnormal values, e.g. dead vines, diseased vines or vines suffering from a localised stress and vines located on the edge of a row or block etc. Nevertheless, the number of missing plants must be accurately estimated in order to upscale any yield that would have been reported at the individual vine scale. This is investigated in particular through remote sensing approaches (Robbez-Masson et al., 2005 ; Primicerio et al., 2017). Taken altogether, the measurements undertaken at the chosen sites should summarize the sampled area in either or both the spatial and attribute spaces. When upscaling measurements, the weight given to each sample site may depend on the number of individuals in the population that it represents. This weight may vary when the variance is not uniform across the block (or sampled area). In most cases, the yield variance is not known, or its spatial structure is unknown, prior to sampling.

Consequently, ensuring a representative criterion for yield or yield components when sampling is challenging. When no *a priori* information on yield is available, methods for targeting sampling sites (stratified sampling schemes) are limited. Sampling design is then often restricted to either a random sampling or to a systematic gridded pattern (Clingeleffer et al., 2001). Both of these options have acknowledged operational bias as the actual sampling sites are not really randomly selected but driven by operator expertise and visual observations. To circumvent this problem, some approaches propose to use stratified sampling schemes by integrating ancillary data, under the hypothesis that there is a relationship between the ancillary data and the yield components or that the ancillary data spatial structure reflects the spatial yield variability. Ancillary data is defined as any variable that provides information on the spatial variability of another variable of interest i.e. yield components in this paper. Ancillary data can then correspond to other yield components, plant ancillary variables or other variables, such as input variables. These data often have the advantage of already being collected or being accessible at a low cost before sampling. In this case, the easily obtained ancillary data, that can be locally related to yield, can be used to help inform sampling designs (Meyers et al., 2020). In the case of grape yield components or yield sampling, ancillary data may correspond to vegetation indices derived from canopy imagery, such as NDVI (Carrillo et al., 2015 ; Meyers et al., 2020) or historical yield data (Araya-Alman et al., 2017). Since the correlation between yield and ancillary data can vary greatly depending on location and time, the use of such data must be carefully considered and integrated (Carrillo et al., 2015). The resolution of the ancillary data, as well as the transformations carried out to upscale the measurement information (aggregations, interpolations, changes in resolution), must be tailored to the objective pursued.

Another point to consider is the ease of travelling from one sample site to another in the field. Most grape blocks are trellised, thus restricting movement across rows within a block. Travel time between sample sites may be considerably increased if the sampling design is poorly organised (Oger et al., 2019). Slopes or difficulties when walking around, such as the absence of grass cover, may also increase the effort required. For these reasons, sampling has to meet a trade-off between the effort or time invested and the desired sampling accuracy. The number of sampling sites needed to achieve sufficient estimation precision depends on the local stochastic variance (Wolpert and Vilas, 1992) and the size of the area sampled. On average, the number of recommended measurements required is in the range of 20 to 30 (Clingeleffer et al., 2001). However, operational constraints do not always permit an operator to achieve a sufficient number of measurements. This recommendation is also based on generating an average yield estimation for a block/vineyard and does not consider the effects of intra-block spatial variance in the yield components.

Review of currently proposed approaches for spatial yield sampling

Different sampling schemes presented in the literature are in use for sampling in agriculture or *a fortiori* in viticulture (Oliver et al., 2013). These approaches can be adapted to all explanatory variables, particularly to yield components. The required sampling effort always needs to be considered in relation to the effort required to measure the yield component.

Random sampling

In a situation where no *a priori* information is available, a random sampling method is generally recommended. This sampling strategy gives each site of the population an equal chance to be selected in the final sample. The lack of information does not allow for the preferential selection of one individual over another, so the choice of sampling sites is therefore completely random. This approach may appear difficult to implement in the field, as randomness is often biased by practical constraints, such as the distances to be covered or the point of entry into the block. Therefore, samples often tend to be located disproportionally close to block edges.

Grid/Systematic sampling

Alternatives to random sampling under conditions with no *a priori* information are based on carrying out measurements on a regular basis. This can be achieved by locating measurement sites on the nodes of a regular grid overlying the block (grid sampling) or by visiting all the rows of the block and carrying out a measurement each time a certain number of vine stocks have been covered (systematic sampling) (Wulfsohn et al., 2010). Regular grid sampling or systematic sampling is open to bias from periodicity in the data e.g. an individual row that was pruned differently or perhaps missed a spray application may be selected and may not be representative of the block. If grid or systematic sampling is used, some degree of randomness needs to be included to minimise this risk.

Target sampling

When available, integrating ancillary data into the sampling design can significantly improve the quality of the estimate. Approaches, such as target (or stratified) sampling, exploit the link between these variables.

Target sampling simply proposes to select sites to be measured based on their ancillary data value. The statistical process for selecting target sites can vary (e.g. using quantiles or *k*-means classification) but with the same objective of defining a set of sampling sites that ensures a certain representativity of the ancillary data distribution. These approaches are widely used, especially in soil studies (Adamchuck et al., 2011) and have been proposed for yield reporting in viticulture (Bramley, 2001 ; Carrillo et al., 2015 ; Meyers et al., 2020) but not widely adopted in commercial vineyards. Some variants, such as the Ranked Set sampling, have also been deployed into other perennial horticultural fruit crops (Uribeetxebarria et al. 2019) or for other vineyard parameters.

Model sampling

Model sampling follows the principles of target sampling but goes further in exploiting the available ancillary data. This sampling strategy uses the observations made at the measurement sites to calibrate the parameters of a model linking the yield variable to the ancillary data. In a second step, the constructed (or newly calibrated) model is used to predict values for the yield variable from the set of available ancillary data. The final estimation is then performed using the mean of all the predicted values. This approach has already been presented for grape yield estimation (Carrillo et al. 2015).

Sampling more complex populations

Other methods are used to sample complex populations that can be divided into subpopulations. The criteria used to form these subpopulations should be selected according to the sampling objectives. For instance, this type of method can be used at the territory scale to select blocks belonging to different areas or at the vine scale to select bunches on different shoots. There are different ways of sampling these populations, such as cluster sampling. Cluster sampling proposes to choose measurement sites by randomly selecting a subpopulation and then an individual from the subpopulation, leaving the freedom to assign different probabilities to sub-population and individuals. The weight assigned to each observation in the final mean may also vary according to the original subpopulations. Some variants of these stratified sampling approaches have already been applied in agronomy (Wulfsohn et al 2010).

Sampling to build a yield map

In certain situations, such as that of selective harvesting, it can be beneficial to build an accurate yield (or yield component) map instead of reporting a mean yield estimation. If this is done from point observations, then the sampling design (number and location of samples) needs to respect limitations with the interpolation method (e.g. kriging or nearest neighbour or inverse distance) and the desired resolution of the map. The same sampling design is not appropriate for estimating mean block statistics and for mapping intra-block spatial patterns. Interpolation and map production tends to require a larger number of samples to generate useful information (e.g. kriging typically requires ~100 samples; Webster and Oliver, 1992) and manually measured yield component maps have only been reported in research studies to date. It is cost prohibitive in commercial situations to map yield estimates from manual measurements, despite the desire to have this information. The need for affordable, timely, higher resolution data to map yield components is a principal reason for the recent activity in the development of on-the-go sensors for yield components.

3.2.4 Issues and methods for yield modelisation

A first requirement for yield modelisation is to properly formulate a model that is adapted to the local conditions of yield development as well as the type of data available to populate the model. Field observations are often collected on the same block over several vintages or on multiple blocks in the same vintage. Assumptions of independence in errors must be respected or taken into account in the modelling approach, for example by using mixed effects (Zhu et al., 2020). When available, data time series analysis should permit the dynamic and time-correlated aspects of yield development to be accounted for. However, most reported studies will typically only study a few punctual indicators that focus on a few phenological stages or time steps, and these data are assumed to be independent but are rarely validated as such (Guilpart et al., 2014 ; Molitor and Keller, 2017). The management of uncertainty, both in terms of the inherent noise (error) in the data itself and in the yield development modelling, must be taken into account, for example by dealing with confidence intervals or even statistical distributions rather than punctual values. Regarding the type of statistical model considered, most reported studies have used a linear model (Dunn and Martin, 2004; Cunha et al., 2016; Zhu et al., 2020). However, a more complete consideration of environmental influences and of the vine-management-environmental dynamics on temporal yield development (accumulation, threshold effect, succession or trajectory effect etc.) is likely to require other, more complex types of models. Models need to permit data to be fitted non-linearly for an explicit aim and be robust to the introduction of new data to extrapolate or expand applications (e.g. Parker et al., 2020). Models based on artificial intelligence methods may be more suitable for this (Sirsat et al., 2019). In such cases, it is not just the model but also the criteria for model selection that needs to be changed. Criteria such as the Akaike or Bayesian information criteria (respectively AIC and BIC) may be preferable to the coefficient of determination (r^2) when assessing model performance. Similarly, models using cross-validation methods (Cunha et al., 2010 and 2016 ; Molitor and Keller, 2017) or evaluating their results on a different validation dataset than the calibration set (Serrano et al., 2005 ; Cunha et al., 2010 and 2016 ; Diago et al., 2012 ; De la Fuente et al., 2015) seem more appropriate. The size of the calibration dataset and the number of different modalities it contains will also give an indication of the adaptability and transferability of the modelling approach.

3.3 Review of yield reporting methods

3.3.1 According to different constitutive steps

Table 6 summaries the different yield reporting methods that have been reviewed. It mainly contains references from the scientific literature, as the methods used by the industry are poorly documented. This is evidence of the fact that commercial wineries still have their own practices and often empirical habits when it comes to yield reporting methods. In Table 6, yield reporting methods are presented according to the use case they address. These use cases are described according to three characteristics : i) the date at which the yield report is provided, ii) the spatial scale at which the yield report is realised and iii) the definition and units that are used to express the final yield. Afterwards, the propositions are split in terms of the measurement and sampling strategies associated with the estimation of the explanatory variables and in terms of modelling the relationship between these variables and final yield. Finally, the experimental datasets that have been used to establish the method are indicated as an appraisal of the reproducibility and robustness of the method in order to properly interpret the results.

The use case in which the method is positioned determines the sources of uncertainty that will have to be managed. The earlier the yield report, the greater the spatial scale of the yield report, the later in the wine production chain that the final yield is defined and/or the more numerous the sources of noise are in the collected data, the more uncertainty will be present. If the method is based on the observation of yield components as explanatory variables, the use case often dictates which components can be sampled according to the timing of the reproductive cycle. For example, only flowers and pollen can be observed at flowering time. Some of these components also define a spatial scale for the yield report. For example, pollen concentration in the atmosphere can only be estimated at a scale greater than or equal to the block, since the plant that produced the collected pollen cannot be identified.

It should be noted that few studies have investigated sampling issues, even though the estimation of yield components at plot scale or larger based on plant observations at the vineyard block scale, or larger scale, is often proposed. Few models based on artificial intelligence have been proposed, perhaps demonstrating a phenomenon that is too complex to be reported in a coherent and interpretable way by these methods, that data sets are too small relative to the phenomenon complexity or that artificial intelligence methods are not yet advanced enough. Non-linear relations thus seem to have mainly been explored by mechanistic models. Data-driven models have focussed on the use of the linear, uni- or multivariate models. Finally, the bias due to data dependency or over-fitting is rarely taken into account since mixed effects or cross-validation methods are rarely used. Results are generally announced in terms of data fitting (r^2) while other selection criteria seem more interpretable from an operational point of view (e.g. Root Mean Square Error).

Table 6 : Methods for yield estimation and prediction reviewed in literature

Use case			Data collection				Modelisation	Experimental dataset	Announced results	Reference
Date	**Spatial scale**	**Yield unit**	**Variables type**	**Explanatory variables**	**Measurement method**	**Sampling method**				
season *n-1*	plant	kg	ancillary plant variables	- leaf predawn water potential - leaf nitrogen content	- water potential : pressure chamber - nitrogen content : destructive measure in laboratory	random sampling	mechanistic modelling	3 seasons 2 blocks 5 treatments, 8 to 30 plants per treatment	r^2 from 0.65 to 0.7 between observed and simulated data	Guilpart et al. 2014
	territorial	hL/ha	ancillary plant variables	NDVI imagery	NDVI : satellite 1 km resolution	no	data driven : linear regression with cross-validation	10 seasons 36 images per season 4 regions of 3x3 km	- r^2 from 0.73 to 0.88 - relative prediction error from 3.8 to 7.8% on validation dataset	Cuhna et al., 2010
- after budbreak, - bloom - after fruitset - close to harvest of season n	block	t	yield decomposition	- various historical yield data - various yield components	manual measurements	random sampling	empirical modelling	1 to 4 seasons 40 blocks	r^2 from 0.40 to 0.95 on calibration dataset	Clingeleffer, 2001
- bloom - veraison - close to harvest of season n	block	kg/ha	input variables	- weather data - phenological dates of bloom, veraison and maturity	unknown	no	artificial intelligence : random forest, lasso, elasticnet, spikeslab	3 seasons, 128 blocks	relative root mean squared error from 24.2 to 28.6%	Sirsat et al., 2019
anytime in season *n*	block	t/ha	input variables	calibration parameters : - weather - soil - crop management - genetic data (see Brisson et al., 2003)	manual measuring	random sampling	mechanistic modelling : STICs	3 seasons, 3 blocks 2 varieties, 5 plant per block	r^2= 0.88 to 0.91 between observed and simulated data	Valdés-Gómez et al., 2009
	intra-block	kg/m	input variables	- weather data - calibration parameters: geography, morphology, soil hydrology, treillis and spacing, canopy and crop management	manual measuring	random sampling	mechanistic modelling	calibration : 2 seasons 1 block, 2 treatments, 4 plants per treatment validation : 5 seasons unspecified blocks	r^2= 0.96 on validation dataset	Cola et al., 2014
	plant	kg	input variables	- weather data - calibration parameters: density, coefficient of light extinction, base temperature, thermal	- manual measuring - literature review	no	mechanistic modelling	2 seasons, 1 block, 1 variety, 60 plants	r^2 = 0.97 between observed and simulated data	Nogueira et al., 2018

				requirements for phenology						
bloom of season *n*	territorial	kg/ha	yield decomposition	airborne pollen	pollen :suction trap with optical microscopic analysis at 10m above ground level	no	data driven : linear regression	5 seasons	r^2=0.92 on calibration dataset	Cristofolini and Gottardini, 2000
		hL	yield decomposition	- airborne pollen - weather data	pollen : filter trap with optical microscopic analysis at 15m above ground level	no	data driven : logistic regression with cross-validation	15 seasons 1 site	-r^2= 0.790 - average relative error = 5.6% on validation dataset	Cunha et al., 2016
between bloom and veraison of season *n*	block	t	yield decomposition	- number of shoots per plant - historical number of bunches per shoot - historical bunch mass	on-board video-analysis	no	mechanistic modelisation	2 seasons 4 blocks 1 video per row	undefined error = 1.2% to 36.0% on calibration dataset	Liu et al., 2017
		t/ha yield map, 3m resolution	ancillary plant variables	- NDVi imagery - LAI imagery	NDVI and LAI : : satellite, 30m resolution	target sampling	data driven : linear regression	2 seasons, 2 blocks	NDVI : r^2 from 0.63 to 0.77 LAI : r^2 from 0.48 to 0.77 on calibration dataset	Sun et al., 2017
	territorial	kg/ha	input variables and yield decomposition	- weather data - number of inflorescences per vine	inflorescences coun : manual	no	data driven : multivariate linear regression with cross-validation	10 seasons, 10 plants, one region	r^2= 0.989 between observed and simulated on validation dataset	González-Fernández et al., 2020
between fruitset and veraison of season *n*	block	kg	input variables	- downy mildew spore concentration and cumulative rainfall	spore : suction trap with optical microscopic analysis at 2 m above ground	no	data driven : multivariate linear regression	6 seasons 1 block 1 variety 20 plants per block	r^2 = 0.98 on calibration dataset	Fernández-González et al., 2011
	intra-block	kg/m	yield decomposition	- historical average bunch mass - average berry mass	manual counting and weighing	no	empirical modelling	4 seasons 14 blocks, 4 rows per block	r^2 from 0.6 to 0.75 of between observed and simulated on validation dataset	De la Fuente et al., 2015
		kg/vine	yield decomposition	bunch count and dimensions	image analysis	target sampling	data driven : linear regression	2 seasons, 1 block 2 zones	r^2=0.82 between observed and simulated data	Di Gennaro et al., 2019
	bunch	g	yield decomposition	bunch dimensions	manually taken pictures on field	no	data driven : linear regression with cross-validation	6 seasons, 4 varieties 50 to 200 bunches per varieties	prediction error from 6 to 15% on validation dataset	Serrano et al., 2005
veraison of season *n*	block	t/ha	yield decomposition	- historical yield maps - post-harvest pruning weight - NDVI imagery - number of buds per plant - number of shoots per plant - number of bunches per plant	- yield : yield monitor installed on harvester - NDVI : satellite imagery, 1-2m resolution - plant components : manual counting, 10m resolution	no	data driven : multivariate linear regression	1 season 9 blocks	r^2 from 0.2 to 0.72 on calibration dataset	Martinez-Casanovas et Bordes, 2005
	plant	kg	ancillary data	weather data	weather station	no	data driven : mixed effects linear regression	15 seasons 4 blocks 8 replicates 4 plants by replicate	r^2=0.8 between observed and simulated data	Zhu et al., 2020
		kg	ancillary plant variables	- NDVI imagery - WI imagery	NDVI : ground-based passive sensing	no	data driven : linear regression	2 seasons, 7 blocks 3 plants per block	NDVI : r^2 up to 0.63 WI: r^2 up to 0.56 on calibration dataset	Serrano et al., 2012 ;González-Flor et al., 2014

close to harvest of season *n*	territorial	hL/ha	input variables	weather data	weather : provided by a national service	no	data driven : window pane analysis and linear regression with cross validation	21 seasons regional production records	r^2=0.82 and 0.85 on calibration dataset	Molitor and Keller, 2017
	block	kg	yield decomposition	proportion of fruit pixels	image analysis in field, manually taken pictures	no	data driven : linear regression	1 season 10 plants with 2 stages of defruitation	0.73 of observed data variability explained by predicted yield for validation dataset	Diago et al., 2012
		kg/plant	yield decomposition	- actual yield per plant - historical geolocalized yield per plant	manual weighing	target sampling	data driven : principal component analysis and linear regression	one season 3 blocks 2 to 10 plots of 5 plants per block	estimation error lower than 10% for more than 5 sampling sites	Araya-Alman et al., 2019
		kg	ancillary plant variables	- NDVI imagery - yield per plant	- manual weighing - NDVI : airborne passive sensin, 0.25m resolution	target sampling	data driven : linear regression with bootstrap	2 seasons, 1 block 54 sites 1m per site	r^2= 0.33 and 0.46 on calibration dataset	Hall et al., 2011
		kg/plant	ancillary plant variables	NDVI imagery	airborne (UAV)	no	artificial intelligence : artificial neuronal network	1 season, 1 block	relative error of 5.1%	Ballesteros et al., 2020
	intra-block	kg/m	yield decomposition	proportion of fruit pixels	on-board image analysis	no	data driven : linear regression	1 season 16 plants with 4 stages of defruitation 1 picture per meter	r^2=0.85 on calibration data set	Dunn and Martin 2004
	plant	kg	yield decomposition	proportion of fruit pixels	on-board image analysis	no	data driven : linear regression	1 season 1 block 1 row of 30 contiguous plants	mean absolute percent of error = 27.8%	Lopes et al., 2016
		kg	yield decomposition	fruit pixel	on board-image analysis	no	data driven : linear regression	1 to 3 seasons 6 blocks	yield prediction error from 2.5 to 29% on calibration data set	Nuske et al., 2014
		t	yield decomposition	- number of nodes per plant -number of bunches per plant - number of berries per bunch - number of seeds per berry - bunch mass, - minimum december temperature	manual counting and weighing	blocks typology according to historical yield level	data driven : linear and non-linear regression	13 seasons 8 blocks 2 rows per block 4 plants per row	mean absolute percent error from 7.3 to 11.8% on calibration dataset	Folwell et al., 1994
	bunch	kg	yield decomposition	proportion of fruit pixels	on board image analysis	no	data driven : linear regression	25 non-occluded bunches	error of 17%	Font et al, 2015

3.3.2 According to identified challenges for improving yield reporting methods in an operational context

Challenges to be addressed by yield reporting methods in an operational context have been identified in the first section of this paper. They are summarized in three categories : i) addressing temporal yield development, ii) addressing yield development as being a local phenomenon and iii) accounting for operational constraints. The main practical implications of these challenges for the establishment of yield reporting methods are detailed in Table 7. They are used to comprehensively compare the methods that have been presented in Table 6.

Few methods have addressed the temporal nature of yield development. There has been no reported use of time-series analysis for yield reporting, regardless of the type of explanatory variables used. Intra-seasonal variables, such as weather variables, are most likely to support time series analysis because of their recording modalities (continuous records daily to 15 minutes time steps). However, most data-driven methods that use weather variables are based on the computation of indicators, e.g. the mean temperature around the bloom period (Zhu et al., 2020) or the amount of rain accumulated during a hundred growing degree days (Guipart et al., 2014), which are considered independent for statistical analysis. Most mechanistic models can be applied at any time of the season as long as the data is available (Valdés-Gómez et al., 2009 ; Cola et al., 2014 ; Nogueira et al., 2018). They are not dynamic models as such, but they can be used to provide yield reports at regular time periods. Finally, there have only been scientific and industrial proposals for yield estimation or prediction methods to date. No yield forecasting method for yield reporting have been proposed yet. This implies that the actual methods in use in operational situations only address part of the uncertainty associated with the elaboration of future yield development and therefore do not meet the operational need to have a yield report that is inclusive of all sources of uncertainty.

The challenge related to the consideration of a local system for yield development is only partly addressed by methods that have worked on improving sampling strategies (spatial or temporal) that can adapt to various local indicators (De la Fuente et al., 2015 ; Araya-Alman et al., 2019). Methods that have worked to improve the measurement of explanatory variables, particularly those that offer automated measurement of yield components, assume the measurement of a specific indicator, which may be different from the indicator historically used by the local vineyard/winery (Lopes et al., 2016 ; Liu et al., 2017). In the reported literature, there is no method that offers to deal with data noise, which comes from a wide variety of sources in the case of operational data. For instance, no attempt has been made at typology to group together data likely to contain the same type of noise or to identify preferred use-cases for adapted modelling methods. This gap clearly shows that scientific viticulture research has yet to address the issue of using operational data to support a yield reporting method.

Most methods have grasped the operational importance of proposing a yield report based on non-destructive (pre-harvest) observations that can be automated. Data-driven methods do assume a number of parameters small enough to be operationally accessible. This is not true for mechanistic methods, whose possibilities of operational implementation are therefore much more limited. Operational implementation is also limited by the fact that about half of the methods reported do not provide a yield report at the spatial scale required by the operational needs, thus forcing the user to upscale the results with limited means and additional sources of uncertainty. Finally, the fact that most of the required equipment is not accessible to the industry, and that most of the methods are not yet commercially implemented, shows that the transfer from scientific research to the industry on the subject of yield reporting is still very restricted.

Table 7 : Comparison of operational advantages of yield estimation and prediction methods reviewed in literature

Reference	Addressing yield development temporality				Locally addressing yield development		Accounting for operational constraints						
	Times series data leveraging	Intra-seasonal variables	Dynamic method	Natural uncertainty management	Data noise management	Adaptive to local indicators	No required upscaling for operational interpretation	Low measuring time	Automatisable	Non destructive	Low number of parameters	Accessible equipement	Already implemented on field
Araya-Alman et al., 2019				estimation		x	x				x	x	
Ballesteros et al., 2020													
Clingeleffer, 2001				prediction		x	x					x	x
Cola et al., 2014		x	x	prediction			x		x	x			
Cristofolini and Gottardini, 2000				prediction			x		x	x	x		
Cuhna et al., 2010		x		prediction			x	x	x	x	x		
Cunha et al., 2016		x		prediction			x		x	x	x		x
De la Fuente et al., 2015				prediction		x						x	x
Di Gennaro et al., 2019													
Diago et al., 2012				estimation				x	x	x	x		
Dunn and Martin 2004				estimation				x	x	x	x		
Fernández-González et al., 2011		x		prediction				x	x	x	x		
Folwell et al., 1994				prediction			x					x	
Font et al, 2015				estimation				x	x	x	x		
Guilpart et al. 2014				prediction						x	x		
Hall et al., 2011				prediction				x	x	x	x		
Liu et al., 2017				prediction			x		x	x			
Lopes et al., 2016				estimation				x	x	x	x		
Martinez-Casanovas et Bordes, 2005				prediction			x						
Molitor and Keller, 2017	x	x		prediction			x	x	x	x	x	x	
Nogueira et al., 2018		x	x	estimation					x	x			
Nuske et al., 2014				prediction				x	x	x	x		
Serrano et al., 2005				estimation						x	x	x	
Serrano et al., 2012 González-Flor et al., 2014				prediction				x	x	x	x		
Sirsat et al., 2019		x		prediction		x	x	x	x		x		
Sun et al., 2017				prediction			x	x	x	x		x	
Valdés-Gómez et al., 2009		x		estimation			x		x	x			
Zhu et al., 2020		x		prediction				x	x	x	x	x	

4. Conclusion : what are the perspectives to improve yield reporting ?

The adaptation of yield reporting approaches to the production conditions of any commercial viticulture enterprise raises interesting scientific questions linked to the management of operational needs, constraints and data that the scientific literature only partially addresses. Based on the assumption that an entire survey of the yield reporting process is required to improve yield reporting in a production context, this paper proposed to review issues and answers in the literature that have already been developed for data collection, including measurement and sampling, and modelisation (cf. Figure 5). Comparing literature contributions to the operational needs and constraints of yield reporting has highlighted the need for new yield reporting methods that are readily transferable to and between commercial, operational systems. Three still unaddressed scientific topics have thus been identified for their potential of yield reporting improvement based on operational data.

4.1 Aiming at operational relevance

First, there is a need to comply with the practical nature of operational constraints, which are common to all vineyards/wineries. This mainly refers to the ease of implementation of the yield reporting methods in the field and interpretability of the provided yield report information. Ease of implementation requires the yield development conceptualization to be as simple and robust as possible and therefore a parsimonious number of accessible indicators to be taken into account. According to the methodology presented by Lamanda et al. (2012), the effects of input and output factors would thus be easier to model and would require fewer parameters to be taken into account. Yield components, which can be considered as outputs of the yield development system, have been foremost and most commonly studied in the literature. Numerous studies have therefore sought to automate their measurement (Diago et al., 2012 ; Nuske et al., 2014 ; Aquino et al., 2015a and 2018b ; Liu et al., 2017) . At this time, these efforts do not allow for an exhaustive measurement of any component, and the observation of yield components therefore remains subject to spatial sampling issues (Carrillo et al., 2015 ; Araya-Alman et al., 2019 ; Oger et al., 2019).

Similarly, with yield components being time-defined and representing evolving indicators of the dynamic process of yield development, their observation also involves temporal sampling issues (Wolpert and Vilas, 1992), which combine biological and operational difficulties (cf. Table 3). Given this, the potential of considering ancillary input factors, such as weather data, that can be continuously and automatically recorded, has been poorly explored (Guilpart et al., 2014 ; Molitor et Keller, 2017 ; Zhu et al., 2020). Yield reporting should benefit from the availability of automated, continuous records that are free from the issues of temporal sampling. Often already available in the vineyards/wineries, these factors could complement or even remove the need for some observations of yield components in the field.

With regard to statistical formalism, an effort of parsimony and robustness should similarly be made for the selection of explanatory variables, which mainly prevents mechanistic models from being used in an operational context (Valdes-Gomez et al., 2009 ; Cola et al., 2014 ; Nogueira et al., 2018).

Good interpretability of yield reports involves providing unequivocal information as accurately as possible. The objective is to remove the need for the user to exercise their judgment, and therefore their subjectivity, in their understanding of the provided yield report. This is achieved by ensuring that sources of uncertainty related to the yield reporting method are already identified and managed. This also implies expressing the expected yield with an operationally used definition and units, i.e. corresponding to the right stage of the production chain, as well as at the correct spatial and temporal scales to avoid the need for up- or down-scaling by the user. These last two points commit to improving knowledge of yield development from both a local and temporal perspective.

4.2 Accounting for yield development temporality

Operational datasets that may support a local modelling of yield development often contain time series. So far in the literature, these times series have been used to compute indicators based on a few phenological stages or time steps and are often considered independent when analysed with linear regression analysis (Guilpart et al., 2014 ; Molitor and Keller, 2017). This approach significantly restricts the potential of time series data analysis by considering only part of the contained information. However, yield development has been recognised in this paper as a dynamic process that includes trajectory or memory effects due to temporal inter-dependencies in grapevine physiology. Thus, the use of novel methods, such as specific or functional time series analysis, could help in further extracting information from time series data. Non-linear relationships could also be investigated in order to improve the modelling of some biological yield-determining phenomena. Such methods could advance the detection of external influences to be primarily considered in a local model of yield development (Laurent et al., 2019) and support the reconceptualization of the actual yield reporting model. However, leveraging time series for yield reporting also requires improved noise reduction methods in the analysis that may be induced by phenological shifts between blocks or years of the same dataset. Computing Growing Degree Days to express time in a more grapevine phenology consistent metric has been a first answer to this issue (Zapata et al., 2015). However, recent work has challenged the way thermal indicators are computed (Parker et al., 2020 ; Camargo-Alvarez et al., 2020) or the time step at which temperature is summarized (Gaiotti et al., 2018 ; Gouot et al., 2019a and 2019b) to model grapevine physiology. This should inspire future work aimed at expressing the timing of grapevine development in a more precise and accurate metric. For the expression of time to be locally relevant, it also seems important to adapt the calculation of these metrics to the block conditions i.e. plant material, pedo-climate, topography, orientation and cultural practices. The date when the reproductive cycle is considered to start may also be reconsidered (Duchêne et al., 2003a ; Vaillant-Gaveau et al., 2014 ; Pagay and Collins, 2017).

The interpretability of a yield report is dependent on an assessment of final yield and not on the currently achieved yield in order to support as far as possible the user in their understanding of the provided yield information. Yield prediction and forecasting methods should therefore be preferred to estimation methods (cf. Figure 4). To the authors' knowledge, only estimation or prediction methods have been proposed in the literature in that sense and current operational models only assume but part of the uncertainty associated with the yield development process. However, yield development is a complex, dynamic process that responds to many interacting influences whose temporal interactions need to be taken into account. Prediction methods only assess the uncertainty in this complexity on the basis of the available dataset, when in reality the range of possibilities (and the level of uncertainty) is much greater. Thus, a significant improvement for yield reporting would be to move towards forecasting methods so as to better inform the user of the uncertainty associated with the provided yield information.

Finally, the literature has identified some key steps in the dynamics of yield development when a portion of final yield variability is fixed by the stable implementation of successive yield components (cf. Figure 3). These steps permit a consideration of what can be expected of yield reporting methods in terms of accuracy. Conducting a yield decomposition analysis (cf. Equation 1) from a temporal perspective on a local dataset should provide an indication on the accuracy that can be expected at each yield component implementation date through the portion of yield variability explained by this component. For example, if the number of bunches per vine is found to temporally and locally explain 40% of final yield variability, then around 40% of accuracy could be expected from yield reporting methods at the date when inflorescences are observed in the field. Such a number should nevertheless be only considered as an approximate indication for reasons of physiological dependencies in the yield development cycle that may affect other, subsequent components (Duchêne et al., 2003b ; Pagay and Collins, 2017). In order to accommodate operational needs and to dynamically monitor yield development, it seems relevant to develop a yield forecast at several dates in the season, with accordingly increasing accuracy and certainty. Depending on the case, these dates could correspond to the progression of certain yield components, to the availability of key ancillary data or to periods that are identified as highly influential at the end of which it would be justified to update the yield forecast.

4.3 Understanding the local organisation of yield development

Operational yield definition, units and scales vary from one vineyard/winery to another. Similarly, there will be enterprise-specific differences in other agronomic indicators and ancillary data that may be collected during the season. As a result of this, the use of operational data in yield reporting models is likely to generate new knowledge on yield development by allowing a wide variety of situations to be studied with large datasets. Data heterogeneity amongst vineyards/wineries should not be a reason for not using operational data in yield reporting. However, a sufficiently general yield development formalisation and reporting method will be necessary to permit the model to adapt to local production conditions. Such a method should be flexible enough to allow for different conceptual schemes of yield development to be considered according to the main external influences and the locally available data, independently of the chosen yield indicators and data quality. It first implies that a dataset must be properly characterized in order to be correctly managed by this method. The aim is to find out what each variable corresponds to, how it has been collected and to assess what level of contribution it might bring to a model as well as its quality i.e. to evaluate the source of uncertainty it may constitute for the yield report. It also means that the main external influences that drive the yield development must be correctly identified in each dataset in order to use them as explanatory variables and to adapt the conceptual model to the local production conditions. To identify such local variables, data-driven approaches may be used to support expert conceptualization. There is a real issue for vineyards/wineries to consolidate data, whose modalities of data collection remain constant over time and space, so that it can be analysed in its entirety as a spatio-temporal dataset and it can rigorously support data-driven approaches. Faced with the growth of artificial intelligence, the challenge for research is also to develop more complete and objective methods if supported by sufficiently large datasets, without losing the possibility of interpreting the results at a local level so that they can be fully exploited from an agronomic point of view.

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