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GeoAI approach to Vineyard Yield Estimation

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PhD

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Abstract

Knowing in advance vineyard yield is a key issue for growers, winemakers, policy makers, and regulators being fundamental to achieve the best balance between vegetative and reproductive growth, and to allow more informed decisions like thinning, irrigation and nutrient management, schedule harvest, optimize winemaking operations, program crop insurance, fraud detection and grape picking workforce demand. In a long-term scenario of perceived climate change, it is also essential for planning and regulatory purposes at the regional level.

Estimating yield is complex and requires knowing driving factors related to climate, plant, and crop management that directly influence the number of clusters per vine, berries per cluster, and berry weight. These three yield components explain 60%, 30%, and 10% of the yield. The traditional methods are destructive, labor-demanding, and time-consuming, with low accuracy primarily due to operator errors and sparse sampling (compared to the inherent spatial variability in a production vineyard). Those are supported by manual sampling, where yield is estimated by sampling clusters weight and the number of clusters per vine, historical data, and extrapolation considering the number of vines in a plot. As the extensive research in the area clearly shows, improved applied methodologies are needed at different spatial scales.

The methodological approaches for yield estimation based on indirect methods are primarily applicable at small scale and can provide better estimates than the traditional manual sampling. They mainly depend on computer vision and image processing algorithms, data-driven models based on vegetation indices and pollen data, and on relating climate, soil, vegetation, and crop management variables that can support dynamic crop simulation models. Despite surpassing the limitations assigned to traditional manual sampling methods with the same or better results on accuracy, they still lack a fundamental key aspect: the real application in commercial vineyards. Another gap is the lack of solutions for estimating yield at broader scales (e.g., regional level). The perception is that decisions are more likely to take place on a smaller scale, which in some cases is inaccurate. It might be the case in regulated areas and areas where support for small viticulturists is needed and made by institutions with proper resources and a large area of influence. This is corroborated by the fact that data-driven models based on Trellis Tension and Pollen traps are being used for yield estimation at regional scales in real environments in different regions of the world.

The current dissertation consists of the first study to identify through a systematic literature review the research approaches for predicting yield in vineyards for wine production that can serve as an alternative to traditional estimation methods, to characterize the different new approaches identifying and comparing their applicability under field conditions, scalability concerning the objective, accuracy, advantages, and shortcomings. In the second study following the identified research gap, a yield estimation model based on Geospatial Artificial Intelligence (GeoAI) with remote sensing and climate data and a machine-learning approach was developed. Using a satellite-based time-series of Normalized Difference Vegetation Index (NDVI) calculated from Sentinel 2 images and climate data acquired by local automatic weather stations, a system for yield prediction based on a Long Short-Term Memory (LSTM) neural network was implemented. The results show that this approach makes it possible to estimate wine grape yield accurately in advance at different scales.

Keywords: Vineyard; Yield; Estimation; Prediction; Forecasting; Systematic Literature Review; Remote Sensing; NDVI; Climate; Machine Learning

Publications

Papers:

Barriguinha, A.; Jardim, B.; de Castro Neto, M.; Gil, A. Using NDVI, climate data and machine learning to estimate yield in the Douro wine region. *International Journal of Applied Earth Observation and Geoinformation* **2022** Vol. 114 Pages 103069. https://doi.org/10.1016/j.jag.2022.103069

Barriguinha, A.; de Castro Neto, M.; Gil, A. Vineyard Yield Estimation, Prediction, and Forecasting: A Systematic Literature Review. *Agronomy* **2021**, *11*, 1789. https://doi.org/10.3390/agronomy11091789

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Abbreviations and Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Networks
BDA	Big Data Analytics
BN	Berry number
CEC	Cation Exchange Capacity
CIVC	Comité Interprofessionel du Vin de Champagne
CNN	Convolutional Neural Network
DSS	Decision Support System
DL	Deep Learning
DM	Data Minning
FMCW	Frequency-Modulated Continuous-Wave
GDD	Growing Degree Day
GeoAI	Geospatial Artificial Intelligence
GNDVI	Green Normalized Difference Vegetation Index
GT	Geo-spatial Technologies
IoT	Internet of Things
LA	Leaf Area
LAI	Leaf Area Index
LiDAR	Light Detection And Ranging
LSTM	Long ShortTerm Memory
ML	Machine Learning
MLR	Multiple Linear Regression
MTVI	Modified Triangular Vegetation Index
NDVI	Normalized Difference Vegetation Index
PA	Precision Agriculture
PDO	Protected Designation of Origin
PGI	Protected Geographical Indication
PLSR	Partial Least Squares Regression
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PS	Proximal Sensing
PV	Precision Viticulture
ReLU	Rectified Linear Unit
RF	Radio Frequency
RFR	Random Forest Regression
RGB	Red Green Blue
RGB-D	Red Green Blue-Depth
RPI	Regional Pollen Index
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SPOT	Satellite Pour l'Observation de la Terre
STICS	Simulateur mulTIdisciplinaire pour les Cultures Standard
Tanh	Hyperbolic Tangent function
TTM	Trellis Tension Monitor
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
UTV	Utility Terrain Vehicle
WI	Water Index
WRELM	Weighted Regularized Extreme Learning Machine
WRELM-TanhRe	TanhRe-based Weighted Regularized Extreme Learning Machine

"Do, or do not. There is no try."

(Yoda)

1. Introduction

This chapter contextualizes the research question, main research goals, and methodological approach. The publications and their relationship with the research design phases are also presented.

1.1 Research context

This dissertation is within the context of information management in the area of Geoinformatics by contributing: first to perceive the research approaches for predicting yield in vineyards for wine production that can serve as an alternative to traditional estimation methods; second, to characterize the different new approaches identifying and comparing their applicability under field conditions, scalability concerning the objective, accuracy, advantages, and shortcomings; third, to identify research gaps for future developments and support a future research agenda on this topic; and fourth, to propose and evaluate a new methodology for estimating vineyard yield at the regional level based on Geospatial Artificial Intelligence (GeoAI), using Normalized Difference Vegetation Index (NDVI) and climate data with a Deep Learning (DL) approach based on a Long Short Term Memory (LSTM) Neural Network.

1.2 Motivation

The European Union is the world-leading producer of wine. Between 2016 and 2020, the average annual production was 165 million hectoliters. In 2020, it accounted for 45% of global wine-growing areas, 64% of production, and 48% of consumption. Wine is the largest EU agri-food sector in exports (7.6% of agri-food value exported in 2020) (Eurostat, 2022b).

Knowing in advance vineyard yield is essential for growers, winemakers, policymakers, and regulators. It is fundamental to achieve the best balance between vegetative and reproductive growth and allow more informed decisions like thinning, irrigation and nutrient management, scheduling harvest, optimizing winemaking operations, program crop insurance, fraud detection, and grape picking workforce demand. In a long-term scenario of perceived climate change, it is also essential for planning and regulatory purposes at the regional level.

The traditional methods (De La Fuente et al., 2015) are considered destructive, labor-demanding, and time-consuming (Diago et al., 2015), with low accuracy (Tardaguila et al., 2013) primarily due to operator errors (Carrillo et al., 2016) and sparse sampling (when compared to the inherent spatial variability in a production vineyard (Nuske et al., 2014b; Sun et al., 2017)).

Those are supported by manual sampling, where yield is estimated by sampling clusters weight and the number of clusters per vine, historical data, and extrapolation considering the number of vines in a plot.

The main efforts towards improved yield models applied to the vineyard are, in most cases, focused on image analysis for grape detection at the field level, with a significant drawback derived from cluster occlusion (Victorino et al., 2020; Whalley and Shanmuganathan, 2013) and considered one of the most complex phenotypic traits in viticulture (Rose et al., 2016). The growing adoption of Precision Agriculture (PA) practices, closely related to the ongoing advances in Geospatial Technologies (GT), Remote Sensing (RS), Proximal Sensing (PS), Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Big Data Analytics (BDA) and Artificial Intelligence (AI) (Boursianis et al., 2020; Hall et al., 2002; Linaza et al., 2021; Sishodia et al., 2020), are fuelling the particular application in Precision Viticulture (PV) (Arnó et al., 2009) where the importance of the wine industry drives the development of innovative methods and technologies to cope with the heterogeneity within vineyards that results from high inter-annual and spatial variability derived from the effects of soil and climate conditions, grapevine variety, biotic and abiotic stresses, vineyard management practices, among others (Hall et al., 2002; Lopes et al., 2016).

But despite being a hot topic in research over the past years it still lacks solutions that can transfer the acquired knowledge and methods to the field and provide tools for wine-growers decision support. Models based on statistically significant relationships between predictors and grapevine parameters are increasingly being overtaken by crop models that can dynamically simulate and integrate into different time frames, plant traits, and other variables regarding management, soil, and climate data (Costa et al., 2015). This is particularly relevant as grape production for wine is closely related to climate variables characterized in the past years by high inter-annual variability with direct adverse effects for wine producers that tend to be amplified by future climate changes' perceived scenarios (Cunha et al., 2015; Fraga et al., 2013; Padua et al., 2019; Sirsat et al., 2019).

Nowadays, zoning the wine production areas, especially in denomination areas, is increasingly becoming more critical for the identification and characterization of homogenous areas that are the basis of regulatory measures over wine (Fernandez-Gonzalez et al., 2011), to allow marketing strategies regarding controlled origins (Shanmuganathan, 2010), and also regarding climate changes that require decisions at a regional level concerning adaptability of different varieties and mitigation management options in one of the most important crops in Europe (Fraga et al., 2016a). PV must apply at the field level and at a larger scale, where the spatial variability may reveal general trends of variation not perceived at more minor scales

(Santesteban et al., 2013). Predicting yield at a larger scale is making more sense now than ever as inter-annual variations attributed to climate change are entering a complex equation where quality, sustainability, efficiency, commercial and marketing strategies, regulations, insurance, stock management, and quotas are all related with yield forecasting (Cunha et al., 2015).

However, there are few examples of yield forecasting at a regional level. Those can be divided mainly into climate-based models estimating grape and wine production (Fraga and Santos, 2017a; Gouveia et al., 2011; Santos et al., 2020a; Sirsat et al., 2019); pollen-based models (Besselat, 1987; Cristofolini and Gottardini, 2000; Cunha et al., 2015; González-Fernández et al., 2020); a combination of one or both with phenological and phytopathological variables (Fernández-González et al., 2011; Fernandez-Gonzalez et al., 2011); STICS models (Fraga et al., 2015); and models based on correlation with indices such as NDVI, LAI, and NDWI (Cunha et al., 2010). All have limitations regarding data acquisition, complexity, applicability, transferability, prediction scale, high maintenance and operational costs, and complex laboratory processes to treat the data. The more commonly used for regional yield estimation are the ones based on the relationship between airborne pollen and yield, relying on the principle that more flowers per area unit in more productive years relates to higher airborne pollen concentrations (Besselat, 1987; Cristofolini and Gottardini, 2000; Cunha et al., 2015; Fernández-González et al., 2011; Fernández-González et al., 2020; Fernandez-Gonzalez et al., 2011; González-Fernández et al., 2020). The main disadvantages/difficulties of using pollen-based models (Barriguinha et al., 2021) are: choosing the best placement for sampling devices to represent effectively spatial variability; the number of observations for model calibration (historical data not commonly available); costly and complex laboratory processes; plant dynamics (high variations of the area with vineyards around the pollen traps); temperature and precipitation variations; vineyard management activities (fertilization impact); and identification of the beginning and final of the pollen season.

In recent years, Deep Learning (DL) has been considered a breakthrough technology in Machine Learning (ML) and Data Mining (DM), including in the RS research field (Zhong et al., 2019). ML methods are increasingly being used as a tool for crop yield prediction (Arab et al., 2021; van Klompenburg et al., 2020), with Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) being the most widely used DL approaches, with better results when compared to traditional ML approaches for crop yield prediction, taking advantage of the ability to extract features from available data (Muruganantham et al., 2022). This data science approach based on Artificial Neural Networks (ANN), despite recent, is not new to vineyard yield estimation and is leading the alternative methods as one of the most utilized techniques for attempting an early yield estimation. However, it has been limited to small-scale experiments, mostly in controlled environments associated with models based on computer vision and image processing (Barriguinha et al., 2021; Mohimont et al., 2022).

GeoAI as a combination of spatial science, AI methods in machine learning (e.g., deep learning), data mining, and high-performance computing to extract knowledge from spatial big data (Kamel Boulos et al., 2019; Vopham et al., 2018) can be applied to the real-world problem such multiple scale vineyard yield estimation.

To the best of the authors' knowledge this thesis represents the first systematic literature review fully dedicated to vineyard yield estimation, prediction, and forecasting methods and the first application of DL to regional vineyard yield estimation.

1.3 Research Focus

Traditional wine grape yield estimation methods (De La Fuente et al., 2015) are destructive, labor-demanding, and time-consuming (Diago et al., 2015), with low accuracy (Tardaguila et al., 2013) primarily due to operator errors (Carrillo et al., 2016) and sparse sampling (when compared to the inherent spatial variability in a production vineyard (Nuske et al., 2014b; Sun et al., 2017)). The importance of the wine industry drives the development of innovative methods and technologies to cope with the heterogeneity within vineyards that results from high inter-annual and spatial variability derived from the effects of soil and climate conditions, grapevine variety, biotic and abiotic stresses, vineyard management practices, among others (Hall et al., 2002; Lopes et al., 2016). Nowadays, zoning the wine production areas, especially in denomination areas, is increasingly becoming more critical for the identification and characterization of homogenous areas that are the basis of regulatory measures over wine (Fernandez-Gonzalez et al., 2011), to allow marketing strategies regarding controlled origins (Shanmuganathan, 2010), and also regarding climate changes that require decisions at a regional level concerning adaptability of different varieties and mitigation management options in one of the most important crops in Europe (Fraga et al., 2016a). PV must apply at the field level and at a larger scale, where the spatial variability may reveal general trends of variation not perceived at more minor scales (Santesteban et al., 2013). Predicting yield at a larger scale is making more sense now than ever as inter-annual variations attributed to climate change are entering a complex equation where quality, sustainability, efficiency, commercial and marketing strategies, regulations, insurance, stock management, and quotas are all related with yield forecasting (Cunha et al., 2015).

The focus herein is to answer the following research questions:

> **What are and can the alternative methods for wine grape yield estimation provide better results to effectively support growers, winemakers, policy makers, and regulators?**
>
> **Can a Geospatial Artificial Intelligence (GeoAI) approach be used to estimate wine grape yield at different scales?**

1.4 Research Goals

The main goals of this thesis include the identification of the different alternative approaches for predicting yield in vineyards for wine production that can serve as an alternative to traditional estimation methods and to develop and evaluate a new methodology for estimating vineyard yield at the regional level based on Geospatial Artificial Intelligence (GeoAI). The results of this thesis were disseminated in computer science conferences and peer-reviewed journal articles.

The main research goals are as follows:

1. Identify the research methodologies for predicting yield in vineyards for wine production that can serve as an alternative to traditional estimation methods.
2. Characterize the different alternative approaches for estimating wine grape yield.
3. Identify and compare the applicability under field conditions, scalability concerning the objective, accuracy, advantages and shortcomings of the different alternative approaches for estimating wine grape yield.
4. Identify research gaps for future developments and support a future research agenda on predicting yield in vineyards for wine production.
5. Propose a new methodology for estimating vineyard yield at the regional level based on Geospatial Artificial Intelligence (GeoAI).
6. Evaluate the new methodology for estimating vineyard yield at the regional level.
7. Publish the results

1.5 Data sources

To reach the proposed goals, the following data sources were used.

1.5.1 Systematic Literature Review

The Scopus, Web of Science, ScienceDirect and IEEE databases were used for the Systematic Literature Review.

1.5.2 Remote Sensing Data

The initial dataset used to produce the temporal NDVI profiles was collected from Copernicus Sentinel-2A and 2B, with a Level-2A of processing level and 10m spatial resolution for 2016-2021. The Sentinel images for the study area were retrieved from the Copernicus Open Access Scientific Hub (https://scihub.copernicus.eu/) from January 11th, 2016, to December 30th, 2021, from which the NDVI was calculated using Band 4 (RED) and Band 8 (NIR).

1.5.3 Climate Data

The climate data used resulted from observed daily values of Average annual total precipitation amount - mm; Average daily air temperature at 1.5m - ^{0}C); Average daily relative humidity - %; and Average daily wind speed – m/s; Average daily global radiation – KJ/m^2, acquired by six IPMA (*Instituto Português do Mar e da Atmosfera* - https://www.ipma.pt/pt/) automatic weather stations between 2016 and 2021.

1.5.4 Phenology Data

Phenology data used to define the different timeframes necessary for the model to predict yield as far in advance as possible effectively for the three main grapevine phenological stages (start): budburst; flowering; and veraison, were collected from the harvest report generated by ADVID (Association for the Development of Viticulture in the Douro Region - https://www.advid.pt/en) between 2016 and 2021.

The harvest start and end dates were collected from the IVDP dataset (Instituto dos Vinhos do Douro e do Porto, I.P. - https://www.ivdp.pt/en) according to the registration of grape entry in the wine-producing facilities between 2016 and 2021.

1.5.5 Yield Data

Yield data was provided by IVDP for each parish from 2016 to 2021. The data was collected yearly in grape reception units scattered along the entire DDR, with the grapes' amount (kg) and origin (parish) recorded for each delivery.

1.6 Methodologies

The study in chapter 2 used the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) statement as a guideline.

The study in chapter 3 used a satellite-based time-series of Normalized Difference Vegetation Index (NDVI) calculated from Sentinel 2 images and climate data acquired by local automatic weather stations, yield data, filtered according to phenology and harvest timeframes, on a Long Short-Term Memory (LSTM) neural network, implemented using the Keras framework.

1.7 Thesis organization

This thesis is structured into four chapters. The first chapter presents the dissertation motivation, the research focus question, the goals, and the methodological approach. The second chapter introduces the systematic literature review on vineyard yield estimation, prediction, and forecasting. In this chapter, the research approaches for predicting yield in vineyards for wine production that can serve as an alternative to traditional estimation methods are reviewed and characterized according to the different approaches identifying and comparing their applicability under field conditions, scalability concerning the objective, accuracy, advantages and shortcomings, allowing to identify research gaps for future developments and support a future research agenda on this topic. The third chapter presents a new model for estimating vineyard yield at the regional level, using NDVI and climate data with a DL approach based on an LSTM Neural Network. This model was validated using real data, and the results are presented and compared with other approaches, including an alternative methodology currently in use in the considered study area. The fourth chapter presents the main findings of the studies described, their contribution, limitations, and future research path.

2. Vineyard Yield Estimation, Prediction, and Forecasting: A Systematic Literature Review

Knowing in advance vineyard yield is a critical success factor so growers and winemakers can achieve the best balance between vegetative and reproductive growth. It is also essential for planning and regulatory purposes at the regional level. Estimation errors are mainly due to the high inter-annual and spatial variability and inadequate or poor performance sampling methods as so improved applied methodologies are needed at different spatial scales. This paper aims to identify alternatives to traditional estimation methods. The study consists of a systematic literature review of academic articles indexed on four databases collected based on multiple query strings conducted on title, abstract, and keywords. The articles were reviewed based on the research topic, methodology, data requirements, practical application, and scale using PRISMA as a guideline. The methodological approaches for yield estimation based on indirect methods are primarily applicable at small scale and can provide better estimates than the traditional manual sampling. Nevertheless, most of these approaches are still in the research domain and lack practical applicability in real vineyards by the actual farmers. They mainly depend on computer vision and image processing algorithms, data-driven models based on vegetation indices and pollen data, and on relating climate, soil, vegetation, and crop management variables that can support dynamic crop simulation models. This work is based on academic articles published before June 2021. Therefore, scientific outputs published after this date are not included. This study contributes to perceiving the approaches for estimating vineyard yield and identifying research gaps for future developments and supporting a future research agenda on this topic. To the best of the authors' knowledge, it is the first systematic literature review fully dedicated to vineyard yield estimation, prediction, and forecasting methods.

2.1 Introduction

With yield being considered a quality grape and wine indicator (De la Fuente Lloreda, 2014; Diago et al., 2015; Santesteban and Royo, 2006; Sun et al., 2017; Zabawa et al., 2019), it is crucial to have an early estimation of the quantity of grapes per area unit. Knowing in advance vineyard yield is a key issue so that growers and winemakers can achieve the best balance between vegetative and reproductive growth; make more informed decisions like thinning, irrigation, and nutrient management; schedule harvest; optimize winemaking operations; program crop insurance fraud detection and grape picking workforce demand (Fernández-González et al., 2011; Fernandez-Gonzalez et al., 2011; Nuske et al., 2014a).

The traditional methods (De La Fuente et al., 2015) are considered destructive, labor-demanding, and time-consuming (Diago et al., 2015), with low accuracy (Tardaguila et al., 2013) primarily due to operator errors (Carrillo et al., 2016) and sparse sampling (when compared to the inherent spatial variability in a production vineyard (Nuske et al., 2014b; Sun et al., 2017)). Those are supported by manual sampling, where yield is estimated by sampling clusters weight and the number of clusters per vine, historical data, and extrapolation considering the number of vines in a plot. The main efforts towards improved yield models applied to the vineyard are in most cases focused on image analysis for grape detection at field level, with a significant drawback derived from cluster occlusion (Victorino et al., 2020; Whalley and Shanmuganathan, 2013) and considered one of the most complex phenotypic traits in viticulture (Rose et al., 2016)

The growing adoption of Precision Agriculture (PA) practices, closely related with the ongoing advances in Geospatial Technologies (GT), Remote Sensing (RS), Proximal Sensing (PS), Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), Big Data Analytics (BDA) and Artificial Intelligence (AI) (Boursianis et al., 2020; Hall et al., 2002; Linaza et al., 2021; Sishodia et al., 2020), are fuelling the particular application in Precision Viticulture (PV) (Arnó et al., 2009) where the importance of the wine industry drives the development of innovative methods and technologies to cope with the heterogeneity within vineyards that results from high inter-annual and spatial variability derived from the effects of soil and climate conditions, grapevine variety, biotic and abiotic stresses, vineyard management practices, among others (Hall et al., 2002; Lopes et al., 2016). But despite being a hot topic in research over the past years it still lacks solutions that can transfer the acquired knowledge and methods to the field and provide tools for wine-growers decision support.

Models based on statistically significant relationships between predictors and grapevine parameters are increasingly being overtaken by crop models that can dynamically simulate and integrate into different time frames, plant traits, and other variables regarding management, soil, and climate data (Costa et al., 2015). This is particularly relevant as grape production for wine is closely related to climate variables characterized in the past years by high inter-annual variability with direct adverse effects for wine producers that tend to be amplified by future climate changes' perceived scenarios (Cunha et al., 2015; Fraga et al., 2013; Padua et al., 2019; Sirsat et al., 2019).Nowadays, zoning the wine production areas, especially in denomination areas, is increasingly becoming more critical for the identification and characterization of homogenous areas that are the basis of regulatory measures over wine (Fernandez-Gonzalez et al., 2011), to allow marketing strategies regarding controlled origins (Shanmuganathan, 2010), and also regarding climate changes that require decisions at a regional level concerning adaptability of different varieties and mitigation management options in one of the most important crops in Europe (Fraga et al., 2016a). PV must apply at the field level and at a larger scale, where the spatial variability may reveal general trends of variation not perceived at more minor scales (Santesteban et al., 2013).

The purpose of the literature review is three-fold: first, to perceive the research approaches for predicting yield in vineyards for wine production that can serve as an alternative to traditional estimation methods; second, to characterize the different new approaches identifying and comparing their applicability under field conditions, scalability concerning the objective, accuracy, advantages and shortcomings, and third, to identify research gaps for future developments and support a future research agenda on this topic.

2.2 Methodology

To identify the relevant scientific work already published on vineyard yield estimation, prediction, and forecasting, a systematic literature review of academic articles indexed on the Scopus, Web of Science, ScienceDirect, IEEE, MDPI, and PubMed databases was carried out, using the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) statement as a guideline (Page et al., 2021). Other databases such as Google Scholar and ResearchGate were not considered because a preliminary study undertaken showed that they would only contribute to a significant increase in duplicate articles.

Depending on the approach, the terminology behind knowing as far in advance as possible the quantity of grapes that will be harvested can be referred to as (1) estimation when the goal is to find the most suitable parameter that best describes a multivariate distribution of a historical dataset; (2) as prediction when a dataset is used to compute random values of the unseen data; (3) and as forecasting when explicitly is added a temporal dimension in a prediction problem. In the present review, the authors adopted the broader term of yield estimation, although the other terms were considered keywords in the search criteria.

The authors adopted a search criteria query string conducted on the title, abstract, and keywords, using all the combinations of the following keywords: "yield" OR "production" AND "estimation" OR "prediction" OR "forecasting" AND "vineyard" OR "grapevine". Only peer-reviewed journals, conference articles, and book chapters were considered for screening.

As the goal is to perceive alternatives to the traditional manual sampling method of determining in advance the vineyard yield, those were excluded from the final data set.

A total of 455 articles published between 1981 and 2021 were found. These articles were reviewed firstly based on title and abstract meeting the search criteria with the inclusion of the indicated keywords, resulting in 239 articles that were retrieved from the respective databases. Further reading resulted in the final 82 records included in the review that verify the research criteria for including scientific studies for vineyard yield estimation, prediction, and forecasting. (Figure 1).

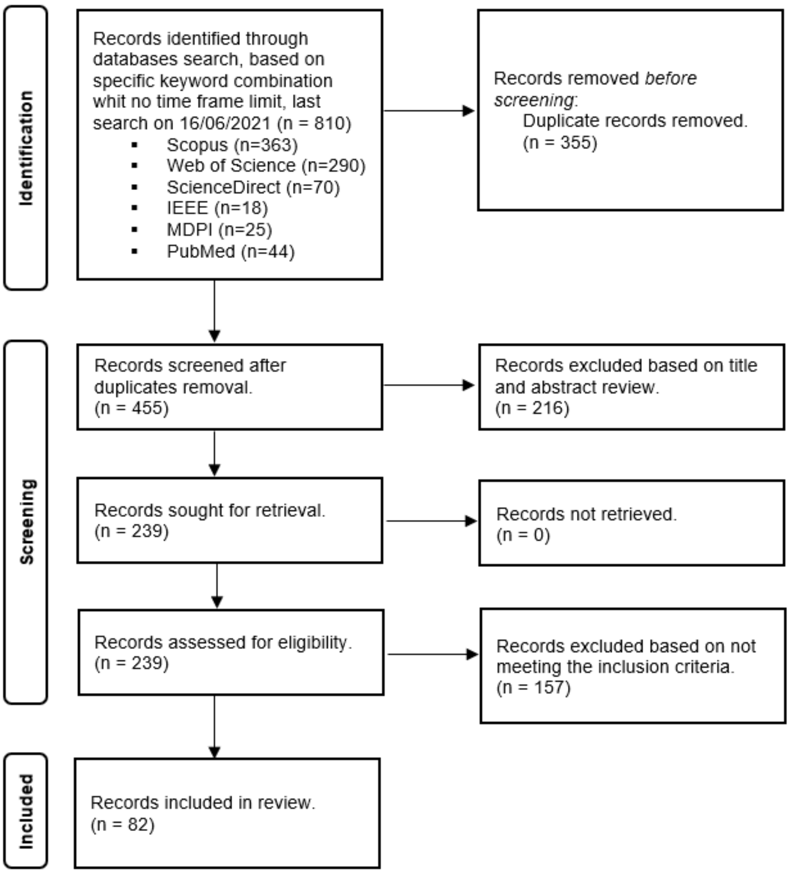

Figure 1 - Systematic Review Procedure for Article Selection.

The final record data set was categorized based on ten different methodological approaches identified for yield estimation in the screening phase that fall into a broader group of indirect estimation models derived mainly from dynamic or crop simulation models and data-driven models. Those were subdivided according to what can be considered more specific approaches.: A - Data-Driven Models Based on Computer Vision and Image Processing; B - Data-Driven Models Based on Vegetation Indices; C - Data-Driven Models based on Pollen; D - Crop Simulation Models; E - Data-Driven Models based on Trellis Tension; F - Data-Driven Models Based on Laser Data Processing; G - Data-Driven Models Based on Radar Data Processing; H - Data-Driven Models Based on RF Data Processing; I - Data-Driven Models Based on Ultrasonic Signal Processing; and J - Other Data-Driven Models. Data regarding the year, authors, keywords, countries, data sources, test environment, applicability scale, and related variables used in estimation and accuracy were evaluated for each methodological approach.

2.3 Results and Discussion

Looking at the scientific peer-reviewed journals distribution it's interesting to see the vast scope of this topic in the researcher's community with publications in 38 different journals, most of them with diverse subjects and scopes, ranging from agronomy to robotics, climate, and sensors. The top six covers 45% of the total papers published, with the remaining 39 (55%) published in 32 different journals (Figure 2).

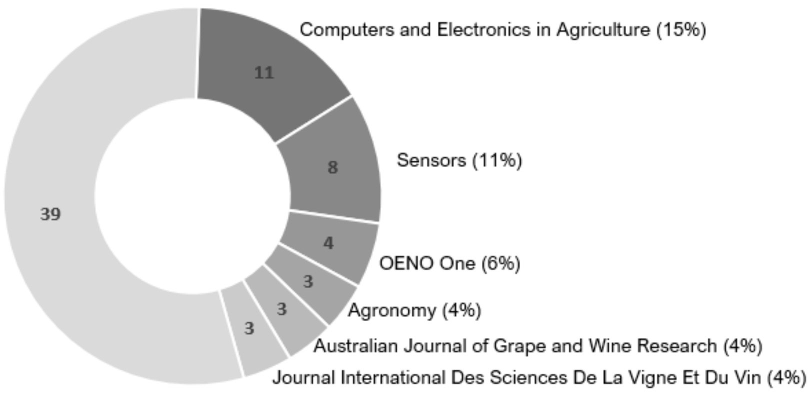

Figure 2 - Distribution according to scientific peer-reviewed journals (top 6 highlighted).

For an overall perception of the ten different methodological approaches identified for yield estimation, they are represented in Figure 3, created with Circos (Krzywinski et al., 2009).

On the right side of the semicircle, we can see the methodologies (from A to J), and on the left side, the years of the publications (from 1987 to 2021 - not considering years in which there are no identified records). The included records are arranged circularly in segments and joined with scaled and colored thickness ribbons to relate the year of publication with the different methodological approaches quantitatively. The relationship between both appears in the inner circle. The thickness and the color represent the percentage of the relationship. Taking the year 2020 as an example, we can see that a universe of 18 records was included in the present review. From those, 11 (61% of the year 2020 records) are related to A (Data-Driven Models Based on Image Processing Algorithms), representing 22% of the 50 records on Data-Driven Models Based on Image Processing Algorithms. Visually we can see that since 2009, there has been a continuous production of articles on this topic, with an increasing interest in research since 2018 with a peak in 2020 (for 2021, the data only covers five months). Regarding methodological approaches, the focus of the researchers dealing with this complex topic is on Data-Driven Models Based on Image Processing Algorithms (A) (61%), followed by Data-Driven Models Based on Vegetation Indices (B) (9%) and Data-Driven Models based on Pollen (C) (9%).

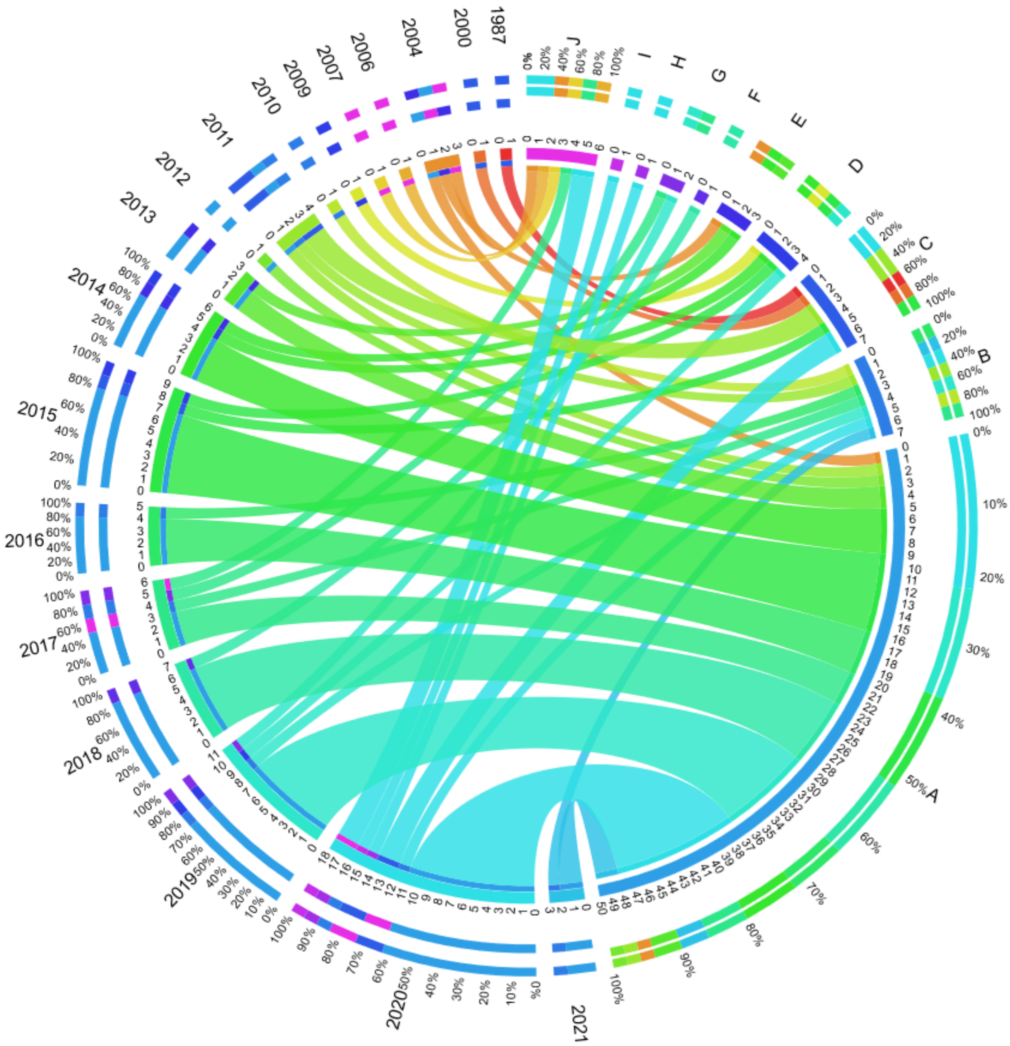

Figure 3 - Representation of the included records, by research methodology and year of publication.

Crop yield estimation has a high degree of complexity. It involves, in most cases, the characterization of driving factors related to climate, plant, and crop management (Weiss et al., 2020) that directly influence the number of clusters per vine, berries per cluster, and berry weight, as the three yield components (Nuske et al., 2014b), explaining 60%, 30% and 10% of the yield respectively (Cunha et al., 2015; Guilpart et al., 2014).The different general methodological approaches used for vineyard yield estimation can be divided firstly regarding the scale (in-field level vs. regional level); and secondly, by direct (based on manual sampling) or indirect methods (statistical models, regression models, proximal/remote sensing, and dynamic or crop simulation models) that depend primarily on image identification and/or related climate, soil, vegetation, and crop management variables (Taylor et al., 2019; Ubalde et al., 2007; Weiss et al., 2020) that can also support crop simulation models, data-driven (Sirsat et al., 2019) and mechanistic growth models (Bindi et al., 1996).

The standard or traditional methods retrieve limited data and produce a static prediction in a multi-step process of determining average number of clusters per vine, number of berries per cluster, and weight per cluster or berry with the growth overall 10% error greatly dependent on adequate staffing and extensive historical databases of cluster weights and yields. (Tarara et al., 2004)

Computer vision and image processing are leading the alternative methods and are one of the most utilized techniques for attempting an early yield estimation. Still, different approaches such as Synthetic Aperture Radar (SAR), low frequency ultrasound (Parr et al., 2020), RF Signals (Altherwy and McCann, 2020), counting number of flowers (Aquino et al., 2015a; Aquino et al., 2015b; Diago et al., 2014; Liu et al., 2018; López-Miranda and Yuste, 2004; Millan et al., 2017; Palacios et al., 2020; Rudolph et al., 2019), Boolean model application (Millan et al., 2018), shoot count (Liu et al., 2017), shoot biomass (Demestihas et al., 2018; Moreno et al., 2020a), frequency-modulated continuous-wave (FMCW) radar (Henry et al., 2019; Henry et al., 2017), detection of specular spherical reflection peaks (Font et al., 2014), the combination of RGB and multispectral imagery (Fernandez et al., 2013) along with derived occlusion ratios, are alternative methods.

Whatever the indirect method used, they all allow a fast and non-invasive alternative to manual sampling. They allow identifying single berries in images, even taken from a simple device like a smartphone (Aquino et al., 2018a; Liu et al., 2020b; Silver and Monga, 2019) and then using different methods such as convolutional neural networks (Santos et al., 2020b; Zabawa et al., 2019), cellular automata (Shanmuganathan et al., 2011), or even sensors capable of collecting phenotypic traits of grape bunches, that are known to be related with grapevine yield (Whalley and Shanmuganathan, 2013; Xin et al., 2020), to estimate yields.

Approaches like non-productive canopy detection using green pixel thresholding in video frames, local thresholding and Self-Organizing-Maps on aerial imagery (Tang et al., 2016); light detection and ranging (LiDAR) for vineyard reconstruction (Moreno et al., 2020b), and map pruning wood (Tagarakis et al., 2018) do not allow direct estimation of the yield but instead provide data layers to relate or use directly or as a correction coefficient in other methodologies, as they can show a relationship to yield.

Indices have been experiencing exponential growth in research related to productive and vegetative parameters in vineyards (Matese and Di Gennaro, 2021; Stamatiadis et al., 2010). Derived from satellite imagery, UAVs (Di Gennaro et al., 2019b; Matese and Di Gennaro, 2021), Unmanned Ground Vehicles (UGVs), or mounted on tractors and Utility Terrain Vehicles (UTVs)(Arnó et al., 2013), Normalized Difference Vegetation Index (NDVI)(Carrillo et al., 2016), Leaf Area Index (LAI) (Arnó et al., 2013; Sun et al., 2017) and Water Index (WI) (with added importance in rainfed vineyards where water deficits play a significant role) (Serrano et al., 2012), are a predictor of spatial yield variability using passive and or active sensors.

Other indirect methods include Bayesian growth models (Ellis et al., 2020); weather-based models (Cola et al., 2014); models based on a combination of variables (meteorological, phenological and phytopathological)(Fernández-González et al., 2011; Fernández-González et al., 2020); dynamic crop model like the “Simulateur mulTIdisciplinaire pour les Cultures Standard” (STICS) (Fraga et al., 2015; Valdes-Gomez et al., 2009); crop biometric maps (Rovira-Más and Sáiz-Rubio, 2013); and the continuous measurement of the tension in the horizontal (cordon) support wire of the trellis (Blom and Tarara, 2009; Tarara et al., 2014; Tarara et al., 2004), also used to determine the best moment of hand sampling for yield estimation (Tarara et al., 2013).

Predicting yield at a larger scale is making more sense now than ever as inter-annual variations attributed to climate change are entering a complex equation where quality, sustainability, efficiency, commercial and marketing strategies, regulations, insurances, stock management, and quotas are all related with yield forecasting (Cunha et al., 2015). However, at a regional level, there are few examples of yield forecasting. Those can be divided mainly into climate-based models estimating grape and wine production (Fraga and Santos, 2017a; Gouveia et al., 2011; Santos et al., 2020a; Sirsat et al., 2019); pollen-based models (Besselat, 1987; Cristofolini and Gottardini, 2000; Cunha et al., 2015; González-Fernández et al., 2020); a combination of one or both with phenological and phytopathological variables (Fernández-González et al., 2011; Fernandez-Gonzalez et al., 2011); STICS models (Fraga et al., 2015); and models based on correlation with indices such as NDVI, LAI, and NDWI (Cunha et al., 2010).

Harvest estimation is a problem to which machine learning, computer vision, and image processing can be applied using one or a combination of techniques (Ballesteros et al., 2020; Maimaitiyiming et al., 2019; Seng et al., 2018). In proximal sensing methods, detection, segmentation, and counting of either individual grapes or bunches are complex in most image-based methodologies (Liu and Whitty, 2015; Parr et al., 2020; Santos et al., 2020b), especially in non-disturbed canopies where occlusion (Coviello et al., 2020; Victorino et al., 2020), illumination, colors, and contrast (Font et al., 2015; Pérez-Zavala et al., 2018) are challenging and in most cases is only demonstrated conceptually in small scale (Liu and Whitty, 2015).

Along with Data Science, Artificial Intelligence, and Deep Learning, vineyard yield estimation can be applied at larger scales, not only through image analysis algorithms but also by identifying relevant predictive variables using data associated with climate, yield, phenology, fertilization, soil, maturation (Palacios et al., 2020; Sirsat et al., 2019) and diseases (Rancon et al., 2019), by making use of a growing number of remote sensing (Cunha et al., 2010) and phenotyping platforms that allow quantitatively assessing plant traits in which yield falls (Kicherer et al., 2015; Milella et al., 2019).

2.3.1 Data-Driven Models Based on Computer Vision and Image Processing

Table 1 shows the summary of the records included in the systematic review regarding the use of computer vision and image processing techniques for yield estimation based on image, recorded mainly with still or mounted standard Red, Green, and Blue (RGB) and RGB- Depth Sensor (D) cameras, for the most under field conditions with local application scale. The main goal is to extract variables from the images that can be related to the actual yield, such as the number of berries, bunch/cluster area, leaf area, number of flowers, stems, and branches. This can be accomplished with various computer vision, machine learning, and deep learning approaches.

From the retrieved results, we can say that computer vision and image processing are the most utilized techniques for attempting an early yield estimation alternatively to traditional sampling methods. The application of this type of methodology mimics for the most the manual sampling, removing the time-consuming and labor demanding tasks of collecting destructive samples from designated smart points that are weighted and used in extrapolation models adjusted with historical data and empirical knowledge from the viticulturist. The process can be divided into the actual data collection – preferably done under field conditions - and the interpretation of the data collected – analyzing the features collected - resulting in a yield estimation.

The images can be acquired using a still camera (Diago et al., 2015; Ivorra et al., 2015; Tardaguila et al., 2013) in a laboratory or under field conditions, and also by other optical or multispectral proximal sensors, on-the-go using ATVs (Aquino et al., 2018b; Nuske et al., 2014b; Palacios et al., 2020), other terrestrial autonomous vehicles (Millan et al., 2018; Nuske et al., 2014a) including autonomous robot systems (Kurtser et al., 2020; Riggio et al., 2018; Victorino et al., 2020), UAVs (Di Gennaro et al., 2019a; Torres-Sánchez et al., 2021) that cope with the limitations of ground vehicles regarding field conditions (slopes and soil) or in a more simple way on foot with a smartphone (Liu et al., 2020b).

Acquiring on-the-go without user intervention represents considerable expectable improvements regarding traditional methods as it allows in the limit to monitor the entire plot autonomously, creating estimation maps at earlier stages that can be updated regularly until harvest, permitting in some cases viticultural practices that can rectify key parameters and facilitate selective harvest (Aquino et al., 2018b). Also, data collection can be made simultaneous with other agronomic operations, reducing acquisitions costs. The data collected can be used to determine multiple parameters directly correlated with yield and cultural practices assessment, vineyard status (Tardaguila et al., 2013), and quality (Ivorra et al., 2015).

The more challenging aspect of the approach is to transform the data collected into an actual yield estimation. The more common approach is to identify automatically individual grapes or clusters for size determination e.g., (Mirbod et al., 2016; Nuske et al., 2011; Tardaguila et al., 2013; Victorino et al., 2020) or other vine structures (Schöler and Steinhage, 2015), along with 3D reconstruction (Herrero-Huerta et al., 2015; Ivorra et al., 2015; Liu et al., 2020b; Marinello et al., 2016; Nellithimaru and Kantor, 2019; Rose et al., 2016; Schneider et al., 2020) to estimate the actual yield . This requires for the most, in the model development phase, training and validation supported by manually assessing cluster weight and berry number per cluster after the image acquisition. The shortcoming related to the traditional approach is that the models are mostly variety dependent, and a commercial solution needs to cope with all the different varieties in a vineyard. According to Millan et al. (Millan et al., 2017), this can be resolved using a base model for identifying flower number per inflorescence that has theoretical potential to be variety-independent. However, according to the same author, the number of flowers per inflorescence alone is insufficient for correct yield estimation and needs to be combined with the fruit set rate and/or the average berry weight. The single variety-independent linear model is also referred by Aquino et al. (Aquino et al., 2015b) but reported by Liu et al. (Liu et al., 2018) as not feasible unless a similarity in both structure and development stage occurs. Different authors, in fact, report flower number as an important explanatory variable for estimating yield (Aquino et al., 2015a; Liu et al., 2018; Palacios et al., 2020) that can give a very early estimative, although not very used in traditional manual approaches as it tends to amplify the already referred shortcomings for cluster sampling.

Another aspect that needs to be pointed out is that a considerable part of the studies was made under laboratory conditions, and the results must be validated under field conditions that are typically very challenging. Also, the ones made "under field conditions" have in some cases more similarities with controlled environments with the vineyard adapted to the methodology and the purposed goal, e.g., counting berry number, instead of the other way around.

One major disadvantage is that 2-D or even stereo images do not bring measurement data in the depth of the scene (Henry et al., 2019), and image analysis algorithms are very dependent on occlusion (Diago et al., 2012; Íñiguez et al., 2021) that can constitute self-occlusions: berries hidden behind berries within the same grape cluster; cluster-occlusions: berries hidden behind other grape clusters; and vine-occlusions: berries hidden behind the leaves and shoots of the vine (Nuske et al., 2014a). Furthermore, environmental dynamics such as leave movements due to wind and changing illumination conditions are challenging when working under field conditions (Nellithimaru and Kantor, 2019). This led some researchers to conduct image acquisition at night time (Nuske et al., 2014b), allowing to isolate vines under evaluation from those in the adjacent row (Aquino et al., 2018b) (more relevant in more defoliated vineyards). Occlusion problems can also be in part resolved detecting the specular reflection peaks from the spherical surface of the grapes from high-resolution images taken under artificial lighting at night (Font et al., 2014) or by using a Boolean model to assess berry number that can estimate partially hidden berries from images collected on-the-go at 7km/h (Millan et al., 2018).

Regarding yield explanatory variables, it is unclear which provide better accuracy as the estimation errors presented vary in the same intervals for different variables. The accuracy seems to be more dependent on the methodological approach used for data collection and the robustness of the algorithms used to derive yield. Comparing the estimation to traditional methods with $0,58<R^2<0,75$ (De La Fuente et al., 2015), this approach can provide better but worse results.

An issue pointed out by some authors (Nuske et al., 2014b) is that management practices (e.g., trellis, leaf-pulling, shoot/cluster thinning and shoot positioning) can directly impact data acquisition, mainly affecting the relation between what is measured and the predicted yield. It means that the choice of methodology must be aligned with the winegrower's type of management.

One important answer to give is how early we can get an accurate yield estimation. Aquino et al. (Aquino et al., 2018b) and Palacios et al. (Palacios et al., 2020) suggested that it is possible to accurately predict yield by monitoring vines at phenological stages between full flowering and cluster-closure (near four months preharvest at the earliest), taking into consideration that a global multi-varietal model requires training large datasets to be operationalized with success. Liu et al. (Liu et al., 2017) go further using video images to detect shoots, allowing for a five months earlier yield estimation that also removes the necessity for prior training using an unsupervised feature selection algorithm combined with unsupervised learning. However, as the author points out, the approach relies heavily on an accurate estimate of the bunch to shoot ratio (time-consuming and prone to selection bias).

Although not much discussed, as all of the different approaches are conducted at a small scale, the use of data-driven models based on computer vision and image processing at larger scales poses a problem regarding computational power (Liu and Whitty, 2015; Rose et al., 2016) that must be addressed to cope with the same limitation already identified in traditional methods regarding poor sampling. Rose et al. (Rose et al., 2016) proposed a pipeline for yield parameter estimation using 3D data for future automated high-throughput, large-data phenotyping tasks in the field.

From the list of methods in Table 1, none is referenced as being used by winegrowers under field conditions in commercial vineyards, even the ones that resulted in APPs, despite the potential still lack the knowledge transfer jump required to help winegrowers.

Table 1 - Summary of records included in the systematic review (Data-Driven Models Based on Computer Vision and Image Processing).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Tardaguila et al., 2013)	Digital still RGB camera	Field/Laboratory	local	Cluster Weight, Berry Number per Cluster, Berry Size, Berry Weight	$0,76<R^2<0,96$ (for all variables)
(Diago et al., 2015)	Digital still RGB camera	Laboratory-based	local	Berry number, Berry weight, Bunch Weight	$0,65<R^2<0,97$ (for cluster weight)
(Ivorra et al., 2015)	Bumblebee2 stereo camera	Laboratory-based	local	Cluster volume and compactness, berry number, size, and weight	$0,71<R^2<0,82$ (for all variables)
(Aquino et al., 2018b)	All-terrain vehicle (ATV) + RGB camera	In-field	local	Berry number	$0,74<R^2<0,78$ RMSE (for yield)
(Palacios et al., 2020)	All-terrain vehicle (ATV) + RGB camera	In-field	local	Number of flowers	$R^2>0,70$ (for yield)
(Nuske et al., 2014b)	All-terrain vehicle (ATV) + RGB camera	In-field	local	Berry detection, number of berries, cluster area, cluster weight	$0,41<R^2<0,75$ (for yield)
(Liu et al., 2017)	Video with Commercial Camera (Go Pro)	In-field	local	Number of grapevine shoots	86.83% (for shoot detection) and 1,18%<error<36,02% (for yield)
(Moreno et al., 2020a)	RGB-D camera (Microsoft Kinect V2 sensor)	In-field	local	Branch volume	$R^2=0,87$ (for yield)
(Diago et al., 2012)	Digital still RGB camera	In-field	local	Leaf area	$R^2=0,73$ (for yield)

(Millan et al., 2017)	Handheld RGB camera	In-field	local	Number of flowers, berry weight	0,49<R^2<0,91 (for yield)
(Íñiguez et al., 2021)	RGB camera	In-field	local	Leaf occlusion, yield, bunch number and bunch weight	0,424<R2<0,871 (for yield)
(Silver and Monga, 2019)	Smartphone camera	In-field	local	Bunch area	0,51<R^2<0,5413 (for yield)
(Liu et al., 2020b)	Smartphone RGB camera	In-field	local	Number of berries per bunch	91% (for berries per bunch)
(Diago et al., 2014)	Digital still RGB camera	Laboratory-based	local	Number of inflorescences	R^2>0,80 (for number of inflorescences)
(Mirbod et al., 2016)	All-terrain vehicle (ATV) + Stereo camera	In-field	local	Berry size, volume, and weight	0,76<R^2<0,96 (for berry weight)
(Liu and Whitty, 2015)	Digital still RGB camera	In-field	local	Bunch area	87 to 90% (for bunch detection)
(Fernandez et al., 2013)	RGB + Multipectral camera	In-field	local	% of leaves, stems, branches, fruits and background	precision: 89.7% (for fruits), 57.2% (for stems), 87.6% (for leaves), 5.4% (for branches)
(Font et al., 2014)	RGB camera at night under artificial lighting	In-field	local	Berry number	Average error=-14% (for number of berries)
(Zabawa et al., 2019)	Phenoliner - Field phenotyping platform	In-field	local	Berry number	87%<berry identification<94%
(Rudolph et al., 2019)	Single-lens reflex (SLR) camera	In-field	local	Number of inflorescences and single flowers	precision<70,7% (for flower extraction)
(Torres-Sánchez et al., 2021)	UAV + RGB camera	In-field	local	Grape cluster area	0,75<R^2<0,82 (for harvest weight)
(Coviello et al., 2020)	Smartphone camera	In-field	local	Berry number	average test error<5% (for berry number)
(Santos et al., 2020b)	Digital still RGB camera	In-field	local	Grape detection	F1-score<0,91 (for instance segmentation)
(Aquino et al., 2015b)	Handheld RGB camera	In-field	local	Number of flowers	0,8588<R^2<0,9912 (for number of flowers)
(Kurtser et al., 2020)	RGB-D camera mounted on a mobile robotic platform	In-field	local	Cluster Size	2.8–3.5 cm average error (for cluster size)
(Milella et al., 2019)	Intel RealSense RGB-D R200 imaging system	In-field	local	Canopy volume, bunch detection and counting	maximum accuracy of 91.52% (for detected fruits)
(Hacking et al., 2019)	2-D RGB and 3-D RGB-D (Kinect sensor)	Field/Laboratory	local	Bunch area and volume	R^2=0,89 (yield with RGB) R^2=0,95 (yield with RGB-D)
(Marinello et al., 2016)	Microsoft Kinect™ RGB-depth	Laboratory-based	local	Bunch volume trough 3D bunch reconstruction	10%<error<15% (for bunch volume)
(Di Gennaro et al., 2019a)	High resolution RGB images (20 MP) taken with a UAV	In-field	local	Cluster number and size	R^2=0,82 (for yield)

(Riggio et al., 2018)	robot with SICK S300 Expert laser scanner + GoPro Hero 4	Field/Laboratory	local	Berry number	$0,55<R^2<0,62$ (for yield)
(Nuske et al., 2014a)	RGB camera + Stereo Camera mounted on UTV	In-field	local	Grapes number	3%<error<4% (for yield)
(Aquino et al., 2017)	Smartphone (BQ Aquaris E5) RGB camera	In-field	local	Berry number per cluster and cluster weight	$0,7485<R^2<0,8292$ (for berry numbers per cluster)
(Tang et al., 2016)	Multispectral Aerial Image + RGB camera (GoPro)	In-field	local	Non-Productive vina canopy	0,77<precision (row)<0,97 (for non-productive canopy)
(Millan et al., 2018)	Cluster images, manually acquired vine images, and vine images captured on-the-go using a quad.	In-field	local	Number of berries in cluster images	$0,50<R^2<0,87$ (for yield)
(Pérez-Zavala et al., 2018)	RGB images	Field/Laboratory	local	Grape berries recognition and grape bunch detection	Grapes bunches detection=88.61%; Single berries>99%.
(Liu et al., 2018)	RGB camera	Field/Laboratory	local	Number of flowers	accuracy of 84.3% (for flower estimation)
(Nellithimaru and Kantor, 2019)	Stereo camera	In-field	local	Dense 3D model of a vineyard and count grapes	$R^2=0,9989$ (for grape count)
(Xin et al., 2020)	2D images from grape bunches	Laboratory-based	local	Three-dimensional grape bunch reconstruction	-0,4%<average percentage error<41,1% (for overall Rachis reconstruction performance)
(Rose et al., 2016)	Track-driven vehicle consisting of a camera system, a real-time-kinematic GPS system (PHENObot)	In-field	local	Quantity of grape bunches, berries, and the berry diameter	Average precision: 97,8% (berry yield)
(Schneider et al., 2020)	Multi-view image datasets from grapes using close-range photogrammetry	Laboratory-based	local	Physical and morphological parameters from 3D grape models	Close-range photogrammetry can be applied to generate 3D grape models parameters such as volume of the grape can be derived from these digital models
(Font et al., 2015)	RGB high-resolution images obtained with artificial illumination at night	In-field	local	Grape-cluster image analysis parameters (area and volume)	Error=16% (for grape cluster area) -16,7% 8for grape cluster volume - 0,3%(average)
(Herrero-Huerta et al., 2015)	RGB images	In-field	local	3d grapevine point cloud, volume, mass and number of berries per bunch	$R^2=0,75$ (for bunch weight)
(Hacking et al., 2020)	RGB camera	Field/Laboratory	local	Bunch volume	$0,70<R^2<0,91$ (for yield)

(Liu et al., 2020a)	RGB images with smartphone camera	In-field	local	3D bunch reconstruction based on a single image	0,82<R^2<0,95 (for berry number) 0,85<R2<0,92 (for bunch weight)
(Aquino et al., 2018a)	RGB images with smartphone camera APP (vitisBerry)	Laboratory-based	local	Berry counting on cluster images	Recall = 0.8762-0.9082 Precision = 0.9392–0.9508
(Aquino et al., 2015a)	RGB images with smartphone camera APP (vitisFlower)	Laboratory-based	local	Number of Grapevine Flowers per Inflorescence	84% of flowers in the captures were found, with a precision exceeding 94%
(Victorino et al., 2020)	Robot with RGB-D Kinect v2 camera and RGB camera	Field/Laboratory	local	Number of spurs, shoots, inflorescences, bunches, berries. Bunch volume, max length, and perimeter	0,29<R^2<0,99 (between bunch weight and other bunch attributes)
(Nuske et al., 2011)	Sideways-facing camera and lighting on UTV	In-field	local	Detect and count grape berries	Predict yield of individual vineyard rows to within 9.8% of actual crop weight
(Dunn and Martin, 2004)	RGB images	In-field	local	Automatically count 'fruit' pixels and the total number of pixels for each image	0,85<R^2<0,99 (for fruit pixels/total image pixels vs fruit weight)
(Di Gennaro et al., 2019b)	High-resolution RGB images, acquired through an unmanned aerial vehicle (UAV)	In-field	local	Number of clusters and size	High accuracy in yield

2.3.2 Data-Driven Models Based on Vegetation Indices

Table 2 shows the summary of the records included in the systematic review regarding the use of data-driven models based on vegetation indices. Remote and proximal sensing are used to measure plant reflected light in different portions of the spectrum allowing the development of various vegetation indices that can provide useful information on plant structure and conditions (Xue and Su, 2017) in a form of mathematical expressions that produces values regarding crop growth, vigor, and several other vegetation properties. There are 519 different indices reported in the Index Database (Henrich et al., 2009). The more recently used in agriculture for yield are listed by Sishodia (Sishodia et al., 2020) and reported as better indicators for full cover crops (e.g., horticulture and cereal) than for discontinuous crops (e.g., olives and vineyards) where, in addition to soil effects, the spectral measurement describes only a part of the canopy, mostly the top (Matese and Di Gennaro, 2021), although regarding soil the impact tends to be low as the vineyard critical growing stage (were indices/yield correlations tend to increase) occurs when cover crops are in most cases, senescent (Sun et al., 2017). For vineyard yield estimation, the records found refer manly NDVI and LAI. (Sishodia et al., 2020; Sun et al., 2017).

Data sources vary mainly from handheld or mounted spectroradiometer (Maimaitiyiming et al., 2019), multispectral cameras mounted on UAV (Matese and Di Gennaro, 2021), or satellite data

(Sun et al., 2017). Each has its own main advantages and disadvantages: spectroradiometers allow a finer sampling with less noise but also a sparser one; UAVs are more practical, fast, and deployed as needed allowing applicability on a medium scale without the disadvantages of satellite temporal, spatial resolution, and cloud coverage dependency; and satellites cover larger areas, and their data can be accessed and processed at low/no cost.

Using hyperspectral reflectance spectra, Maimaitiyiming et al. (Maimaitiyiming et al., 2019) propose an in-depth study to address the effects of irrigation level and rootstocks on vine productivity. As part of the study, vine productivity, including fruit yield and ripeness parameters, were measured with 20 vegetation indices calculated and used as input for predictive model calibration. The berry yield and quality prediction models were developed with multiple linear regression (MLR), partial least squares regression (PLSR), random forest regression (RFR), weighted regularized extreme learning machine (WRELM) and a new activation function by fusing of hyperbolic tangent (Tanh) function and rectified linear unit (ReLU) for WRELM (WRELM-TanhRe), demonstrating moderate to relatively strong correlations between berry yield and vegetation indices, namely water index (WI) (r = 0.67) modified triangular vegetation index (MTVI) (r=0,64) and green normalized difference vegetation index (GNDVI) (r = 0.53). Regarding yield estimation, RFR outperformed the different models' calibration (R^2 = 0,86), while in the validation test, the WRELM-TanhRe model achieved the highest estimation accuracy (R^2 = 0,62).

Indices as NDVI can also strengthen traditional manual sampling trough informed sampling strategies that may mitigate errors resulting from the within-field variability, improving yield estimation on average by 10% using NDVI data (Carrillo et al., 2016)

Using satellite data allows for regional scale estimation that can cover large areas. Gouveia et al. (Gouveia et al., 2011) developed multi-linear regression models of wine production, using NDVI and meteorological variables (monthly averages of maximum, minimum, and daily mean temperature and precipitation) as predictors to estimate yield in a 250000 hectares region with R^2=0.62 for early season estimation and R^2=0,90 for mid-season. A similar approach was made by Cunha et al. (Cunha et al., 2010) with Satellite Pour l'Observation de la Terre (SPOT) ten-day synthesis vegetation product (S10) for three different regions in Portugal with significant interannual variability, based on a correlation matrix between the wine yield of a current year and the full set of 10-day synthesis NDVI.

Although the recognized potential of NDVI, Matese et al. (Matese and Di Gennaro, 2021) argues that acquiring and analyzing spectral data, besides costly (multispectral cameras), requires skills ("spectral know-how on radiometric correction and data analysis, primarily for filtering the canopy with low-temperature sensors resolution from common multispectral cameras") not often available for all farmers. As an alternative, a model based on geometric data (canopy thickness and volume) retrieved with RGB sensors outperformed NDVI data. However, the authors' statements can be debated as low-cost NDVI cameras are becoming more available, namely Agrocam (https://www.agrocam.eu/) and Mapir (https://www.mapir.camera) both with powerful and easy to use free cloud software included, although the data quality can be argued and requires validation and comparison with more recognized commercial multispectral alternatives pricier but also with more features as, DJIMultispectral (https://www.dji.com/pt/p4-multispectral), Micasense (https://micasense.com) Parrot Sequoia+ (https://www.pix4d.com/product/sequoia) and Sentera (https://sentera.com/data-capture/6x-multispectral/). Ballesteros et al. (Ballesteros et al., 2020) used a hybrid approach combining NDVI (reflectance approach) with vegetated fraction cover as a measure of plant vigor (geometric approach) resulting in higher accuracy when compared to simple NDVI use with good results but requiring calibration for each season.

An important question is the time frame for data acquisition to give the best correlation day to estimate yield. Matese et al. (Matese and Di Gennaro, 2021) collected data during three seasons in the veraison phenological stage; Carrillo et al. (Carrillo et al., 2016) before veraison; Ballesteros et al. (Ballesteros et al., 2020) made UAV flights in several stages: fruit set, berry pea size, veraison, final berry ripening and after harvest. Maimaitiyiming et al. (Maimaitiyiming et al., 2019) collected data during the late veraison stage and the fruit ripening stage with the dates determined based on the number of no-rain days after irrigation treatment initiation (considering that the study was not focused only on yield estimation). For NDVI Gouveia et al. (Gouveia et al., 2011) identified through comparing NDVI cycles and meteorological parameters for years of low and high wine production significant differences during three stages: (1) from dormancy; (2) from budbreak and (3) starting with flowering and continuing during veraison, with a maximum at the end of spring and a minimum during winter for the selected vineyard area pixels, also indicating that good years for wine production reflect high photosynthetic activity during the previous autumn and spring followed by reduced greenness and reduced growth during summer (considering the Douro region in Portugal where the study was conducted). Sun et al. (Sun et al., 2017) found similar performance in NDVI and LAI regarding spatial yield variability, with peak correlations during the growing season that differed in different years. Maximum and seasonal-cumulative vegetation showed slightly lower correlations to yield. The authors state that the best time interval depends on the crop type, climate/weather conditions and management practices. Cunha et al. (Cunha et al., 2010) used NDVI measurement 17 months before harvest with very good results in obtaining very early forecasts of potential regional wine yield (model explained 77– 88% of the inter-annual variability in wine yield).

In line with what has already been mentioned for the data-driven models based on computer vision and image processing this approach can provide better results on estimation yield. As pointed out by Sun et al. (Sun et al., 2017), performance is very dependent on environmental conditions and management strategies. For satellite data, spatial resolution can be the major bottleneck in smaller scales (Cunha et al., 2010) along with less flexibility derived from temporal resolution and soil effect (Ballesteros et al., 2020). However, presently there are alternatives like Sentinel-2 with 12 spectral bands in 10-20 m spatial resolution, with global coverage and a 5-day revisit frequency.

Table 2 - Summary of records included in the systematic review (Data-Driven Models Based on Vegetation Indices).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Maimaitiyiming et al., 2019)	Vegetation indices derived from canopy spectra	In-field	local	Vegetation indices derived from canopy spectra	$0,52<R^2<0,68$ (for berry yield and quality parameters)
(Gouveia et al., 2011)	Corine Land Cover map, wine statistics, monthly means of climate variables and NDVI	Simulated	Regional	tmax, tmin, tavg, prec, NDVI	$0,62<R<0,90$ (for wine production)
(Matese and Di Gennaro, 2021)	UAV multispectral camera	In-field	local	NDVI, Canopy Geometry-Based Indices	$R^2<0,85$ (for yield)
(Sun et al., 2017)	Satellite-based (NDVI) and (LAI)	In-field	Regional	NDVI, LAI	$0,66<R<0,83$ (for NDVI and Yield) and $0,66<R<0,83$ (for LAI and Yield)
(Carrillo et al., 2016)	Multispectral airborne imagery	In-field	local	NDVI, berry weight at harvest, bunch number per vine, and berry number per bunch	$-0,04<r<0,81$ (for NDVI vs yield)
(Cunha et al., 2010)	Satellite data from vegetation (NDVI from SPOT)	In-field	Regional	NDVI	$0,73<R^2<0,84$ (for yield)
(Ballesteros et al., 2020)	Quadcopter md4-1000 with a multispectral Sequoia camera	In-field	local	Radiometry and geometry-based parameters (NDVI and Fc), water regime, fertilization, climate data	$0,60<R^2<0,96$ (for yield)

2.3.3 Data-Driven Models based on Pollen

Table 3 shows the summary of the records included in the systematic review regarding the use of data-driven models based on pollen. These models rely on the relationship between airborne pollen and yield (Besselat, 1987). The assumption is that there are more flowers per area unit in more productive years, thus higher airborne pollen concentrations (Cunha et al., 2015).

Pollen monitoring and the determination of the pollen index (annual sum of the daily pollen concentrations in m^3/year) was done by Cristofolini et al. (Cristofolini and Gottardini, 2000) between the days when 5 and 95% of the seasons total pollen concentration were found (between 12 and 29 days per season) with very good results (R^2=0,92). The combination of aerobiological, phenological, and meteorological data used by Gonzaléz et al. (González-Fernández et al., 2020) and Fernandez et al. (Fernández-González et al., 2011; Fernández-González et al., 2020; Fernandez-Gonzalez et al., 2011) also allowed an accurate production estimated more than one or two months in advance, with Fernandez et al. (Fernández-González et al., 2020) achieving better results from an hirst trap (volumetric) for local predicting and with cour (passive) trap for regional yield predictions. Cunha (Cunha et al., 2015) made a more comprehensive study to assess the model adaptability in fast expanding regions (regarding area and technology) with non-irrigated areas, with heavy water and thermal stress during summer. The study resulted in a regional forecast model to determine the potential yield at flowering through airborne pollen concentration and climate impact, applied to Alentejo in Portugal (one of the aridest wine regions of Europe). The determined regional pollen index (RPI) and fruit-set data as explanatory variables allowed a very good regional estimation (R^2=0,86)

Choosing the best placement for sampling devices at the regional level representing effectively spatial variability, the number of observations needed for model calibration (usually years as historical data, as opposed for instance to weather data, is not commonly available), costly and complex laboratory processes, plant dynamics (e.g., high variations of the area with vineyards around the pollen traps) are the main disadvantages of using data-driven models based on pollen (Cunha et al., 2010; Cunha et al., 2015). The number of pollen traps must be related to the area of influence and the availability of grapes or wine production at the relevant spatial scale (Cunha et al., 2015). Rainfall and temperature (primarily average and maximum) have an influence on pollen season, and so in pollen index values, typically higher temperature increases pollen concentration in the vineyard, and rainfall leads to less airborne pollen concentrations (Cristofolini and Gottardini, 2000; Fernández-González et al., 2020). Also, fertilization during the flowering period can negatively decrease the airborne pollen concentrations (González-Fernández et al., 2020). For regional estimative, the models' performance is linked with the different approaches on calculating RPI, and special care must be taken regarding the identification of the beginning and final of the pollen season to avoid pollen deposition, recirculation, and long-distance transport that does not contribute effectively to local pollination but increases RPI (Cunha et al., 2015).

In line with what has already been mentioned above these approaches can provide better results on estimation yield with application to local and regional scales.

Table 3 - Summary of records included in the systematic review (Data-Driven Models based on Pollen).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Cristofolini and Gottardini, 2000)	Hirst type sampler volumetric spore trap (Lanzoni VPPS-2000)	In-field	Regional	Airborne pollen concentration	R^2=0,92 (for grape production)
(Fernandez -Gonzalez et al., 2011)	Aerobiological data (Lanzoni VPPS-2000 volumetric trap)	In-field	Regional	Meteorological and phytopathological variables	R^2=0,98 (for yield)
(Fernández -González et al., 2020)	Pollen Hirst volumetric sampler and Cour passive trap	In-field	Regional	Airborne pollen concentration, weather data	R^2=0,96 (Cour); R^2=0,99 (Hirst)
(Besselat, 1987)	Pollen concentration data	In-field	Regional	Airborne pollen concentration	R^2<0,98 (for yield)
(Cunha et al., 2015)	Airborne pollen trap	Simulated	Regional	Airborne pollen concentration	0,71<R^2<0,86 (for annual wine production)
(Fernández -González et al., 2011)	Aerobiological (Lanzoni VPPS-2000 volumetric trap) Phenological (BBCH standardized scale) Meteo data	In-field	local	Meteorological, phenological and phytopathological variables	0,79<R^2<0,99 (for yield)
(González-Fernández et al., 2020)	Aerobiological data (Lanzoni VPPS-2000 volumetric sampler), Meteorogical data	In-field	Regional	Airborne pollen concentration and Meteorologic data	R^2=0,99 (for yield)

2.3.4 Crop Simulation Models

Table 4 shows the summary of the records included in the systematic review regarding the use of crop simulation models. Crop models are important decision-support systems in agriculture (Fraga et al., 2016a) that allow the simulation through mathematical equations of plant development and the interaction with the environment by integrating phenotypic traits along with climate, soil, management decisions, and others variables considered to be related to yield estimation in this particular case. This approach is becoming more popular because it allows for virtual experiments that can be made in a specific phenological stage testing hypothesis that could take years under real field conditions. Another advantage is the possibility of integrating decision support systems (DSS) (Cola et al., 2014; Fraga et al., 2015).

The retrieved studies are complex and not limited to yield estimates as they simulate grapevine growth and development. The models need to be appropriately calibrated and validated. That is one of the disadvantages of using this approach, as it needs to be adapted for new environments with distinct climate, soil, grapevine varieties, training systems and management. As so, complexity and cost in terms of time and biophysical data requirements turn operationality and transferability very difficult (Sirsat et al., 2019).

The model developed by Cola et al. (Cola et al., 2014) achieved good results in a five-year validation assessment demonstrating flexibility and thrift regarding meteorological data. The approach used to simulate the fruit load was based on light interception derived gross assimilation and thermal and water limitations.

Sirsat et al. (Sirsat et al., 2019) focused on grape yield predictive models for flowering, coloring and harvest phenostages (due to lack of data regarding other phenostages, namely setting, berries pea-size and veraison) using machine learning techniques and climatic conditions, grapevine yield, phenological dates, fertilizer information, soil analysis and maturation index data to construct the relational dataset. The authors stated that meteorology data is the critical element for measuring the quantity of grapes, as the derived features of dew point, relative humidity, and air temperature were identified as the most favorable variables in constructing the model.

Some models like the STICS have been used for different types of crops with good results: Fraga et al. (Fraga et al., 2015) used it for three Portuguese native varieties. The application of this model requires thorough parameterization regarding yield components and historical phenological data computed by STICS using a concept called growing degree day (GDD). The results for simulating yield demonstrated a good capability of the model, with an overestimation in one of the regions studied and underestimation in the other. The authors pointed out a critical factor related to the duality between quality and yield and the need for viticultural practices such as cluster thinning to be included in the model parametrization. The same model was used by Valdes et al. (Valdes-Gomez et al., 2009) in non-irrigated and irrigated vineyards in Chile and France, with similar results for yield estimation with an overestimation, that resulted from the underestimation of moderate water stress simulated by STICS after veraison.

Table 4 - Summary of records included in the systematic review (D - Crop Simulation Models).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Cola et al., 2014)	Weather data and plant characteristics	Simulated/In-field Validation	Regional	Weather data and plant characteristics	R^2=0,96 (for yield in low-density canopies) R^2=0,94 (for yield in high-density canopies)
(Fraga et al., 2015)	Climate, soil, and management practices	Simulated/In-field Validation	Regional	Climate data, soil and terrain parameters, water stress indices, management practices	R^2=0,86 (for yield)
(Valdes-Gomez et al., 2009)	Phenology and harvest date, Soil water content, water stress, and grapevine growth and yield	Simulated/In-field Validation	Regional	Phenology and harvest date, soil water content, water stress, and grapevine growth and yield	R^2=0,85 (for yield)
(Sirsat et al., 2019)	Weather, yield, phenological dates, fertilizer information, soil analysis, and maturation index data	Simulated/In-field Validation	Regional	Weather, phenological dates, fertilizer information, soil analysis, and maturation index data	24,2%<RRMSE<28,6%

2.3.5 Data-Driven Models based on Trellis Tension

Table 5 summarizes the records included in the systematic review regarding using data-driven models based on trellis tension, all from the same author. This approach is an indirect real-time method that uses sensors in the wires to measure the production in each vine row. The changes in tension are recorded by automated data systems connected to the load cells installed in-line. Each line needs calibration, the data must be corrected to remove the effects of temperature (using a 48 h moving average), and the effects of wind gust are negligible because measurements are not made in continuous periods (Tarara et al., 2004). The linear regression found in the studies demonstrates good results and estimation with better results than the traditional manual sampling.

The trellis tension methodology can also be used to determine the timing for traditional hand sampling for yield estimation to determine the lag phase, thus eliminating the field scouting subjective visual and tactile assessments to assess whether berries are at lag phase (Tarara et al., 2013).

Despite the better estimative that can be achieved and the ability to monitor near to real-time, the applicability of this method to commercial vineyards still needs to be evaluated regarding, needed calibration for different vineyards and trellis systems, consistency across seasons, installation costs, number of sensors and spatial deployment (Tarara et al., 2004).

The trellis tension monitor (TTM) as a spatial response to removing uniformly distributed fruit load of up to ~24 m or ~12 m to either side of the sensor. This means that 8 to 10 vines are a meaningful sample size (Tarara et al., 2014).

Table 5 - Summary of records included in the systematic review (E - Data-Driven Models based on Trellis Tension).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Tarara et al., 2004)	Load cells installed in−line with the cordon wire	In-field	local	Tension in the horizontal (cordon) support wire of the trellis	0,99<R^2<0,99 (for tension and yield)
(Tarara et al., 2013)	Tension Sensor in main load-bearing wire	In-field	local	Timing for hand sampling	nd
(Tarara et al., 2014)	Trellis Tension Monitors (TTMs)	In-field	local	Tension in the horizontal (cordon) support wire of the trellis	0,81<R^2<0,98 (for yield)

2.3.6 Data-Driven Models Based on Laser Data Processing

Table 6 shows the summary of the records included in the systematic review regarding using data-driven models based on laser data processing with only one study identified. Vine canopy properties are a good indicator of quality and yield (Tagarakis et al., 2018). The application retrieved shows the potential of laser scanner technology to collect plant geometric characteristics with sufficient precision capable of being correlated with yield using a shoot sensor called Physiocap®, de-signed and developed by the CIVC (Comité Interprofessionel du Vin de Champagne) that maps vigor spatial variability used during winter just before pruning (Demestihas et al., 2018). In this study, the authors refer that at the scale of the Champagne (region in France where the study was conducted) vineyard, the aboveground biomass estimation was strongly correlated with the yield of the following year. The estimation results are good, but extreme climate events tend to lower the correlation found at a more local scale. Being the only study regarding this approach and dependent on data from a single region that has been collected since 2011, applications to other regions must be evaluated.

Table 6 - Summary of records included in the systematic review (F – Data-Driven Models Based on Laser Data Processing).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Demestihas et al., 2018)	Physiocap® - optical laser	In-field	local	Shoot biomass	R^2=0,98 (for yield)

2.3.7 Data-Driven Models Based on Radar Data Processing

Table 7 summarizes the records included in the systematic review regarding the use of data-driven models based on radar data processing, all from the same author. 3-D radar imagery techniques for yield determination are reported here as an alternative to remote estimations based on proximal optical or multispectral proximal or remote sensors to deal with limitations regarding performance, occlusion, and light issues in field conditions.

Henry et al. (Henry et al., 2019; Henry et al., 2017) used ground-based frequency-modulated continuous-wave radars operating at 24, 77, and 122 GHz to contact-less estimate grape mass. The major advantage is that most grapes can be detected under field conditions even if leaves, shoots, or other grapes partially or fully hide them. As for limitations, the study only addressed yield estimation at the maturation phase for five different varieties.

Table 7 - Summary of records included in the systematic review (G - Data-Driven Models Based on Radar Data Processing).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Henry et al., 2019)	3-D radar imagery (FM-CW radar)	In-field	local	Polarization and magnitude of radar echoes	$0,79<R^2<0,97$ (for yield)
(Henry et al., 2017)	24 GHz frequency-modulated continuous-wave (FMCW) radar	In-field	local	Grapes in grapevines from the radar echoes distribution in the interrogated 3D scene	$R^2=0,947$ (for grape volume)

2.3.8 Data-Driven Models Based on Radio Frequency Data Processing

Table 8 shows the summary of the records included in the systematic review regarding the use of data-driven models based on radio frequency data processing, with only one record retrieved. It relies on a new exploratory approach using a scheme that senses grape moisture content by utilizing Radio Frequency (RF) signals to estimate yield without physical contact in a laboratory environment. According to the authors, it can be used for early yield estimation(Altherwy and McCann, 2020). The study represents an exploratory approach in a laboratory environment that does not provide an actual yield estimative. Therefore, its applicability to real world scenarios needs to be addressed. Nevertheless, it could be an alternative path for one of the main issues reported in data-driven models based on computer vision and image processing, occlusion.

Table 8 - Summary of records included in the systematic review (H - Data-Driven Models Based on Radio Frequency Data Processing).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Altherwy and McCann, 2020)	RF signals	Laboratory-based	local	Grape moisture content	Degree of accuracy=90% (for moisture content)

2.1.9 Data-Driven Models Based on Ultrasonic Signal Processing

Table 9 summarizes the records included in the systematic review regarding the use of data-driven models based on ultrasonic signal processing, with only one record retrieved. Using low-frequency ultrasound is an alternative approach to detect grape clusters in the presence of foliage occlusion at a lower cost compared to alternatives like Synthetic Aperture Radar (SAR) (Parr et al., 2020). Despite not being a study to determine yield and, being developed in a laboratory environment, the results are very interesting as they can provide an alternative for one of the main issues reported in data-driven models based on computer vision and image processing which is occlusion.

Table 9 - Summary of records included in the systematic review (I - Data-Driven Models Based on Ultrasonic Signal Processing.).

Reference	Data Sources	Test environment	Scale	Related Variables	Estimation
(Parr et al., 2020)	Ultrasonic Array	Laboratory-based	local	Grape cluster detection	Ability to propagate through foliage and reflect of grapes behind

2.3.10 Other Data-Driven Models

Table 10 summarizes of the records included in the systematic review that did not fall into one of the previous identified groups.

For regional level decision support, Fraga et al. (Fraga and Santos, 2017b) proposed a simple grape production model based on favorable meteorological conditions. This model runs on a daily step, comparing the thermal/hydric conditions in a given year against the average conditions in high and low production years in three regional wineries, allowing one to perceive regional heterogeneity. The recognition of the importance of climate data for estimating yield at the regional level was also addressed by Santo et al. (Santos et al., 2020a) with an empirical model where temperature and precipitation averaged over the periods of February–March, May–June, and July–September, along with the anomalies of wine production in the previous 5 years, were used as predictors. At a local level, both climate and soil data were considered by Ubalde (Ubalde et al., 2007) as yield predictors, with Cation Exchange Capacity (CEC) and Winkler Index providing the best correlations with similar importance.

A different approach was made by Ellis (Ellis et al., 2020), collecting bunch mass data during three seasons and using a Bayesian growth model, assuming the double sigmoidal curve that characterizes grape growth according to literature, to predict the yield at the end of those seasons. The author advocate using Bayesian methods due to the capability of systematically incorporate prior knowledge and update the model with new data. The study is not very clear regarding yield estimation and does not indicate the accuracy.

By determining water status, leaf area (LA), and fruit load influence on berry weight (BW) and sugar accumulation, Santeesteban et al. (Santesteban et al., 2013) found that average leaf water potential in summer and LA/BN ratio, when considered together, estimated BW properly (R^2 = 0,91), showing that under semiarid conditions, water availability plays the primary role in regulation of berry growth.

Table 10 - Summary of records included in the systematic review (J - Other Data-Driven Models).

Reference	Data Sources	Test environment	Applicability Scale	Related Variables	Estimation
(Fraga and Santos, 2017b)	Daily historic meteorological conditions, yield data	In-field	Regional	Temperature and Precipitation	$0,68 \leq r \leq 0,84$ (for grapevine production)
(Ubalde et al., 2007)	Edapho-climatic data	In-field	Local	Cation exchange capacity (CEC), Winkler index	R^2=0,88 (CEC and Winkler Index for yield)
(López-Miranda and Yuste, 2004)	Number of flowers per cluster, fruit-set percentage, berry weight	In-field	Local	Number of flowers per cluster, fruit-set percentage, berry weight	$0,54<R^2<0,93$ (for number of flowers and yield)
(Santos et al., 2020a)	Monthly mean air temperatures and monthly total precipitation data	Simulated	Regional	Monthly mean air temperatures and monthly total precipitation	Wine production classes (1-low, 2-normal, 3-high): average estimation ratio of 79%(calibration) 67%(validation)
(Ellis et al., 2020)	Bunch mass data	In-field	Local	Bunch mass data	n.d.
(Santesteban and Royo, 2006)	Leaf area, berry number, yield, water potential in summer, berry weight, sugar concentration	In-field	Local	Leaf area, berry number, yield, water potential in summer, berry weight, sugar concentration	LA/BN ratio estimated properly BW (R^2 = 0,91))

2.4 Final Considerations and Future Work

As an overall conclusion, the alternative methodologies for yield estimation mentioned in this paper can, as demonstrated by the revised articles, surpass the limitations assigned to traditional manual sampling methods with the same or better results on accuracy. They all have advantages and shortcomings, but more importantly, they still lack a fundamental key aspect: the real application in a commercial vineyard.

Despite extensive research in this area, adoption at an operational level to effectively substitute the manual sampling estimation is residual. Methods made available to winegrowers should estimate production as far in advance as possible must be as simple as possible and with little data as possible, preferably with data that producers can access quickly, easily, and cheaply and if possible, without the need for intensive training or validation. The best approach must consider the availability and/or possibility to have the required inputs (required data is sometimes not available), the adequate spatial resolution (field level or regional level), the necessary granularity (information regarding the spatial variability in each area) and required precision (e.g., a simple smartphone camera, despite the loss in quality, can be in many cases a cost-effective alternative to hyper and multispectral cameras, LiDAR, ultrasonic and radar sensors).

The synergistic use of proximal and remote sensing with AI can be one of the best ways to model a vineyard production system. Still, due to its inherent complexity, it is a difficult challenge to apply because of the diversity of field conditions, as remote sensing data is dependent on spatial, temporal, and spectral resolution; and yield is correlated with an extensive list of climate, soil and plant variables that have high temporal and spatial heterogeneity. Also, the relation to quality is one of the biases that yield estimation needs to deal with, as the producer's management decision directly impacts both quality and yield.

For local estimation at the farm level, data-driven models based on computer vision and image processing are the ones the researcher's community is putting more effort and can be classified as the easiest to deployed by growers under real field conditions. Data acquisition can be made easily on the go with a vast array of solutions ranging from a simple smartphone to an autonomous robot platform, a UAV, or even agriculture equipment. Despite good results in estimating yield, these methods are not fully matured yet. Management practices (e.g., trellis, leaf-pulling, shoot/cluster thinning and shoot positioning) can directly impact data acquisition by affecting the relationship between what is measured and the predicted yield. There are still problems with occlusion, algorithms are generally variety dependent, and environmental dynamics are challenging. Data acquisition speed, computational processing constraints, and the availability of predictive yield maps as output should be addressed in commercial applications.

Vegetation indices are also a good alternative as they can be easy to deploy and used at different scales with good results, especially NDVI. Data acquisition is, generally feasible, and affordable, but transforming data into usable information requires technical knowledge not often available for all farmers. The past limitations linked to the direct use of multispectral satellite remote sensing data, such as insufficient spatial resolution, inadequate temporal resolution, and complex data access and processing, were significantly overcome since the launch in mid-2015 of the EU Copernicus Program' Sentinel-2 mission combined with the development of appropriate desktop and cloud-based data processing platforms (e.g., Google Earth Engine: https://earthengine.google.com/ (Johnson and Mueller, 2021); Sen2-Agri: http://www.esa-sen2agri.org/ (Defourny et al., 2019); and Sen4CAP: http://esa-sen4cap.org/(López-Andreu et al., 2021)). As for models based on computer vision and image processing, correspondent operational solutions are not yet available for growers as needed. Future commercial solutions can pass by including yield estimation algorithms in UAVs data management software or web platforms like EO Browser (https://apps.sentinel-hub.com/eo-browser/) or EOS Platform (https://crop-monitoring.eos.com/) providing multispectral satellite data and derived products and indices, with required parametrization when needed.

Crop models were also referenced as one of the best alternatives for estimating yield. Still, few examples were identified, mainly because of the complexity of their development, especially hard in vineyards because of the inherent specificities and the required data for calibration in different locations and for different varieties.

There is also a lack of solutions for estimating yield at broader scales (e.g., regional level). The perception is that decisions are more likely to take place at a smaller scale, which in some cases is not accurate. It might be the case in regulated areas and areas where support for small viticulturists is needed and made by institutions with proper resources and a large area of influence. This is corroborated by the fact that data-driven models based on Trellis Tension and Pollen traps are being used for yield estimation at regional scales in real environments in different regions of the world.

Other more residual approaches like laser, radar, radio frequency and ultrasonic data can provide new alternatives to cope with some of the difficulties encountered especially in computer vision and image processing approaches.

Despite the use of remote and proximal sensing models with an inherent spatial component, predictive yield maps are scarcely referenced and used as an output of yield estimation models. New approaches like GeoAI (Janowicz et al., 2020) are not yet referred to in the reviewed articles. As spatial variability and heterogeneity are some of the more critical parameters for decision-making in PV (the producer wants to know the quantity and where that quantity is), it is a relevant research gap that must be addressed appropriately.

3. Using NDVI, climate data and machine learning to estimate yield in the Douro wine region

Estimating vineyard yield in advance is essential for planning and regulatory purposes at the regional level, with growing importance in a long-term scenario of perceived climate change. With few tools available, the current study aimed to develop a yield estimation model based on remote sensing and climate data with a machine-learning approach. Using a satellite-based time-series of Normalized Difference Vegetation Index (NDVI) calculated from Sentinel 2 images and climate data acquired by local automatic weather stations, a system for yield prediction based on a Long Short-Term Memory (LSTM) neural network was implemented. The study was conducted in the Douro Demarcated Region in Portugal over the period 2016-2021 using yield data from 169 administrative areas that cover 250,000 ha, in which 43,000 ha of the vineyard are in production. The optimal combination of input features, with an Mean Absolute Error (MAE) of 672.55 kg/ha and an Mean Squared Error (MSE) of 81.30 kg/ha, included the NDVI, Temperature, Relative Humidity, Precipitation, and Wind Intensity. The model was tested for each year, using it as the test set, while all other years were used as input to train the model. Two different moments in time, corresponding to FLO (flowering) and VER (veraison), were considered to estimate in advance wine grape yield. The best prediction was made for 2020 at VER, with the model overestimating the yield per hectare by 8%, with the average absolute error for the entire period being 17%. The results show that with this approach, it is possible to estimate wine grape yield accurately in advance at different scales.

3.1 Introduction

Because yield is a quality grape and wine indicator (De la Fuente Lloreda, 2014; Diago et al., 2015; Santesteban and Royo, 2006; Sun et al., 2017; Zabawa et al., 2019) an early estimation allows growers to find the best balance between vegetative and reproductive growth and make better management and planning decisions (Fernández-González et al., 2011; Fernandez-Gonzalez et al., 2011; Nuske et al., 2014a) that can directly impact the business model.

Estimating yield is complex and requires knowing driving factors related to climate, plant, and crop management (Weiss et al., 2020) that directly influence the number of clusters per vine, berries per cluster, and berry weight. These three yield components (Nuske et al., 2014b) explain 60%, 30%, and 10% of the yield, respectively (Cunha et al., 2015; Guilpart et al., 2014).

The different approaches for vineyard yield estimation depend on the scale of implementation, and from there, direct (based on manual sampling) or indirect methods (statistical and regression models, proximal/remote sensing, and dynamic or crop simulation models) are used (Bindi et al., 1996; Sirsat et al., 2019; Taylor et al., 2019; Ubalde et al., 2007; Weiss et al., 2020). The first represent the traditional method (De La Fuente et al., 2015) susceptible to spatial and temporal variability and dependent on historical data (Victorino et al., 2022), costly and time consuming (Diago et al., 2015), with low accuracy (Tardaguila et al., 2013) and limited to small-scale application. On the other hand, indirect methods can cope with the limitations off the traditional manual sampling methods and with better results on accuracy, despite the low adoption in real commercial vineyards (Barriguinha et al., 2021).

At a regional level, the vineyard yield estimation goals are more related to regulation and monitoring activities (Barriguinha et al., 2021), with yield estimation becoming more and more relevant due to inter-annual variability attributed to climate change's impact on quality, sustainability, efficiency, commercial strategies, regulations, and management of insurance, stock, and quotas (Cunha et al., 2015; K. Newlands, 2022). The decisions made on this scale can have a large impact, especially in terms of vineyard area and the number of producers involved. A clear example are the Wine Protected Designation of Origin (PDO) label as an European quality scheme that protects high quality wines by linking them to legally defined geographic areas and a set of specific production practices that covers 21 countries (Candiago et al., 2022) with more than 2,1 million hectares of PDO vineyards (Eurostat, 2022a).

From previous works, the authors found few examples of yield estimation for regional scales (Barriguinha et al., 2021), divided mainly into climate-based models (Fraga and Santos, 2017a; Gouveia et al., 2011; Santos et al., 2020a; Sirsat et al., 2019); pollen-based models (Besselat, 1987; Cristofolini and Gottardini, 2000; Cunha et al., 2015; González-Fernández et al., 2020); a combination of one or both adding phenological and phytopathological variables (Fernández-González et al., 2011; Fernandez-Gonzalez et al., 2011); Simulateur mulTIdisciplinaire pour les Cultures Standard, or multidisciplinary simulator for standard crops (STICS) models (Fraga et al., 2015); and models based on correlation with Vegetation Indices (VI) (Arab et al., 2021; Cunha et al., 2010). Only a few are referenced for real environment, producing estimation for decision-making (Barriguinha et al., 2021).

The more commonly used for regional yield estimation are the ones based on the relationship between airborne pollen and yield, relying on the principle that more flowers per area unit in more productive years relates to higher airborne pollen concentrations (Besselat, 1987; Cristofolini and Gottardini, 2000; Cunha et al., 2015; Fernández-González et al., 2011; Fernández-González et al., 2020; Fernandez-Gonzalez et al., 2011; González-Fernández et al., 2020). The main disadvantages/difficulties of using pollen-based models (Barriguinha et al., 2021) are: choosing the best placement for sampling devices to represent effectively spatial variability; the number of observations for model calibration (historical data not commonly available); costly and complex laboratory processes; plant dynamics (high variations of the area with vineyards around the pollen traps); temperature and precipitation variations; vineyard management activities (fertilization impact); and identification of the beginning and final of the pollen season.

Another relevant approach for large areas is the combination of meteorological data and Remote Sensing (RS), based on satellite imagery products such as VI to effectively estimate in advance vineyard yield (Cunha et al., 2010; Gouveia et al., 2011; Sun et al., 2017), with VI explaining crop characteristics and climatic conditions directly influencing crop yield prediction (Muruganantham et al., 2022).

Regarding climate, wine grapes are susceptible and dependent on a region's climatic environment and weather dynamics, with climatic variables impacting vine and grape growth and development (Anderson et al., 2012; Badr et al., 2018; Fraga et al., 2013). Precipitation, humidity, temperature, radiation, and wind have the more influence grapevine phenology, yield, and wine quality (Badr et al., 2018; Parker et al., 2022; Santos et al., 2012).

VI, as mathematical expressions corresponding to values of growth, vigor, and other vegetation properties, can be derived from satellite time-series images (Di Gennaro et al., 2019b; Matese and Di Gennaro, 2021) and are related to vineyard productive and vegetative parameters including yield (Matese and Di Gennaro, 2021; Stamatiadis et al., 2010; Xue and Su, 2017). These indices have been widely implemented within remote sensing (RS) applications (Murali et al., 2021; Snevajs et al., 2022) using multiple satellite platforms. Giovos et al. (Giovos et al., 2021) traced their origin to 1968 with RVI (Birth and McVey, 1968) and in 1973 with NDVI (Rouse et al., 1974). There are unlimited combinations for creating different VI, but regarding viticulture, NDVI is the most used (Giovos et al., 2021). The Index Database (Henrich et al., 2009) has over 500 different indices extensively used in applications of RS for precision agriculture (Sishodia et al., 2020), with the Normalized Difference Vegetation Index (NDVI) considered a critical parameter (Carrillo et al., 2016; Pelta et al., 2022) capable of reliable yield prediction models (Arab et al., 2021). For discontinuous crops such as a vineyard, proximal data acquisition with spectroradiometers (Maimaitiyiming et al., 2019) or with multispectral cameras mounted on Unmanned Aerial Vehicles (UAV) (Matese and Di Gennaro, 2021) can overcome the limitations attributed to satellite data, namely the soil effects (low for the vineyard as the critical growing stage - were indices/yield correlations tend to increase - occurs when cover crops are in most cases, senescent (Sun et al., 2017)), cloud coverage, or the fact that spectral measurement only describes the top part of the canopy, being nevertheless of limited use in large areas due to sparse sampling and high acquisition costs. Gouveia et al. (Gouveia et al., 2011) developed multi-linear regression models of wine production, using NDVI and meteorological variables as predictors to estimate yield (e.g., monthly averages of maximum, minimum, and daily mean temperature and precipitation). A similar approach was made by Cunha et al. (Cunha et al., 2010) with *Satellite Pour l'Observation de la Terre* (SPOT) ten-day synthesis vegetation product (S10) for three different regions in Portugal with significant interannual variability, based on a correlation matrix between the wine yield of a current year and the full set of 10-day synthesis NDVI.

In recent years, Deep Learning (DL) has been considered a breakthrough technology in Machine Learning (ML) and Data Mining (DM), including in the RS research field (Zhong et al., 2019). ML methods are increasingly being used as a tool for crop yield prediction (Arab et al., 2021; van Klompenburg et al., 2020), with Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) being the most widely used DL approaches, with better results when compared to traditional ML approaches for crop yield prediction, taking advantage of the ability to extract features from available data (Muruganantham et al., 2022). This data science approach based on Artificial Neural Networks (ANN), despite recent, is not new to vineyard yield estimation and is leading the alternative methods as one of the most utilized techniques for attempting an early yield estimation. However, it has been limited to small-scale experiments, mostly in controlled environments associated with models based on computer vision and image processing (Barriguinha et al., 2021).

The purpose of the present paper is two-fold: first, to evaluate a new methodology for estimating vineyard yield at the regional level, using the Douro Demarcated Wine Region as a study area with readily available data, and allowing transferability to other regions, to give decision-makers, as far in advance as possible, a good estimation, not only for the total regional and sub-regional wine grape production areas but also at a more detailed scale, considering three sub-regions and 169 sub-administrative regions where there are vineyards in production. Secondly, to cope with the limitations identified in the current model in use in the study area, based on the work of Cunha et al. (Cunha et al., 2003; Cunha et al., 1999), which relies on the relationship between airborne pollen and wine production, namely: predicting only for the entire region; predicting wine production instead of wine grape production; the need to maintain representative pollen sampling devices with high maintenance and operational costs, and complex laboratory process to treat the data; and a wide prediction interval. The proposed model using NDVI and climate data with a DL approach based on a Long Short Term Memory (LSTM) Neural Network can produce an adequate estimation of wine grape yield up to 1-2 months before harvest. To the best of the authors' knowledge, it is the first application of DL to regional vineyard yield estimation.

3.2 Materials and methods

3.2.1 Study area

The study was carried out using the different datasets described in the next points, covering six years (2016-2021). The study area is covered by the Douro Demarcated Wine Region (DDR), which is the oldest wine-demarcated region in the world. It is located in the northeast of Portugal (Figure 4) in the Douro watershed, surrounded by complex terrain with unique orographic, mesological and climatic characteristics. The region extends over a total area of about 250,000 ha and is divided into three naturally distinct sub-regions ("Baixo Corgo", "Cima Corgo" and "Douro Superior"), not only due to climatic factors but also socio-economic ones. Regarding regulatory purposes, the DDR has some specificities. From the total area planted with vines (about 43,000ha), only 26,000ha are authorized to produce Port Wine. In fact, the vineyards suitable for production are selected according to qualitative criteria (classified through a scale) that consider soil, climate, and cultural parameters with decisive importance in the qualitative potential of the plots. Only vineyards with more than five-year-old can be considered for producing Port Wine. According to the cadastral elements, each plot is entitled to a certain benefit coefficient that needs to be determined every year and indexed to the classification scale. The vineyard areas are divided into 104,000 individual plots (47% on "Cima Corgo"; 39% on "Baixo Corgo", 14% on Douro Superior) spread into 169 administrative regions called "Freguesias" (Parishes). These were considered for the present study as the minimum scale areas for grape yield estimation, followed by the sub-regions and the entire DDR.

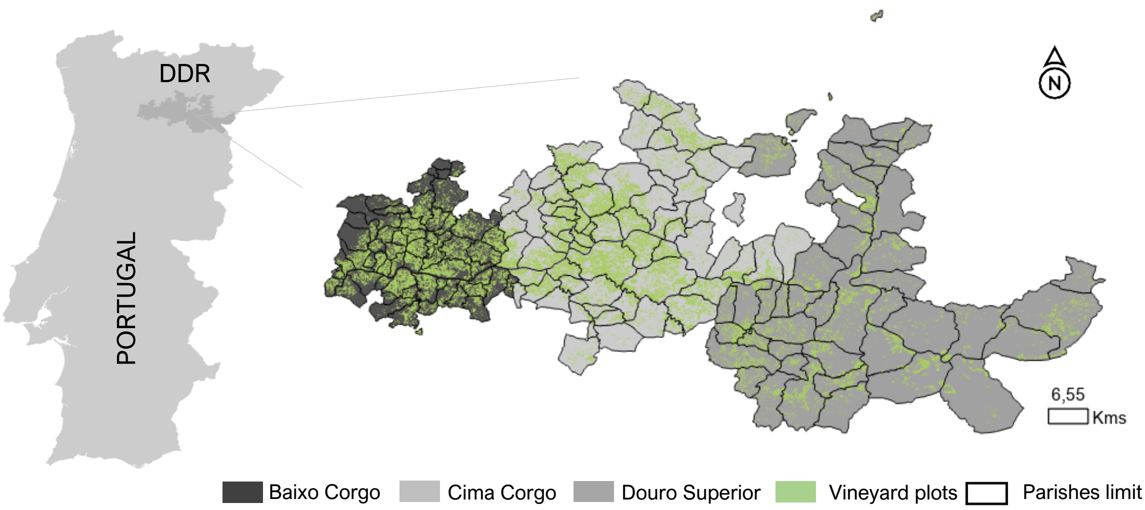

Figure 4 - Study area overview with the three sub-regions, vineyard plots locations (provided by the IVV - Instituto da Vinha e do Vinho, IP (Portuguese Institute of Vine and Wine), and 169 administrative regions considered for the present study as the minimum scale areas for grape yield estimation

Each year the vineyard area in production varies since there are new areas, areas not yet in production, and areas considered unsuitable for producing wine with denomination of origin. This was considered for the present study due to the impact on determining the grape yield per area unit (kg/ha) for each year and each parish. Table 11 shows the aggregated data for the three sub-regions and the entire DDR.

Table 11 - Vineyard area distribution in the DDR sub-regions (2016-2021)

Year	BC (57 parishes)			CC (64 parishes)			DS (48 parishes)			DDR (169 parishes)		
	sum	avg	sd	sum	avg	sd	sum	avg	sd	sum	avg	sd
2016	12808	224.7	165.7	19700	307.8	318.5	9598	200.0	171.0	42106	249.1	240.0
2017	12842	225.3	166.2	19778	309.0	319.9	9600	200.0	170.4	42220	249.8	240.8
2018	12794	224.5	165.0	19899	310.9	322.9	9661	201.3	174.0	42354	250.6	242.8
2019	12740	223.5	164.9	19958	311.8	325.8	9684	201.7	175.3	42382	250.8	244.6
2020	13202	231.6	171.1	20429	319.2	334.2	10078	210.0	181.4	43709	258.6	251.3
2021	12966	227.5	166.5	20510	320.5	335.7	10207	212.6	182.1	43683	258.5	251.3

BC (Baixo Corgo sub-region); CC (Cima Corgo sub-region); DS (Douro Superior sub-region); DDR (Douro Demarcated Region); sum (productive vineyard area - hectare); avg (average productive vineyard area/parish – hectare); sd (standard deviation)

3.2.2 Remote sensing data

For the present study, the initial dataset used to produce the temporal NDVI profiles was collected from Copernicus Sentinel-2A (launched on June 23rd, 2015) and 2B (launched on March 7th, 2017), with a Level-2A of processing level and 10m of spatial resolution, for the period 2016-2021. A total of 686 usable Sentinel images were retrieved from the Copernicus Open Access Scientific Hub (https://scihub.copernicus.eu/), corresponding to 343 different acquisition dates (two images per acquisition date due to the study area extension), from January 11th, 2016, to December 30th, 2021, from which the NDVI was calculated using Band 4 (RED) and Band 8 (NIR) as described in equation 1.

$$NDVI = (NIR - RED)/(NIR + RED) \tag{1}$$

Where: NIR is the reflectance in the near-infrared channel and RED is the reflectance in the red channel.

From the initial dataset, as explained in 3.2.4, only values between March (when on average, budburst occurs, marking the beginning of seasonal grapevine growth and resumed physiological activity) and October (when most of the harvest has already taken place) were considered (Table 12). Those were used to build a spatiotemporal cube by clipping the areas of each parish with the vineyard in production, resulting in the average NDVI values for each parish at each date used in the model described in 3.2.6.

Table 12 - Descriptive statistics of NDVI data from the entire DDR for the areas with vineyards (2016-2021) – from March to October

Year	CC		MIN		MAX		MEAN		PCT90	
	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd
2016	34.8	39.0	0.026	0.062	0.648	0.224	0.303	0.126	0.420	0.165
2017	23.7	32.1	0.009	0.070	0.603	0.218	0.250	0.117	0.348	0.153
2018	25.3	33.7	-0.002	0.086	0.628	0.222	0.275	0.136	0.393	0.176
2019	30.3	34.0	-0.002	0.076	0.569	0.242	0.233	0.129	0.334	0.172
2020	42.5	37.5	-0.006	0.096	0.540	0.283	0.234	0.154	0.332	0.202
2021	34.0	35.6	0.001	0.077	0.606	0.241	0.272	0.139	0.385	0.182

CC (Average Cloud Coverage - %); MIN (Average Minimum NDVI value); MAX (Average Maximum NDVI value); MEAN (Average NDVI value); PCT90 (Average NDVI value 90 percentile); sd (standard deviation)

With both satellite data, the best average temporal resolution for the study area is five days from 2018, 2020, and 2021 (71 images retrieved) followed by 2019 with six days (60 images retrieved). The lower temporal resolutions in 2016 (15 days – 25 images retrieved) and 2017 (8 days – 43 images retrieved) are related to the inexistence of the Sentinel-2B sensor until March 2017.

Regarding the expected negative effect of cloud coverage, we first considered all images for conducting the evaluation of the yield prediction model through a stepwise backward feature selection process, thus allowing us to assess the true impact and the limit to which we might consider the validity (or not) of each image.

3.2.3 Climate data

The DDR climate is the Mediterranean, with continental influence and marked annual thermal contrast and water stress, especially during summer with the vineyards located in some of the aridest regions in Europe, with strong and consistent post-flowering vine water and thermal stress (Cunha et al., 2010).

The climate data used in the present study resulted from observed daily values of the parameters described in Table 13 acquired by six IPMA (*Instituto Português do Mar e da Atmosfera* - https://www.ipma.pt/pt/) automatic weather stations between 2016 and 2021. The considered areas of influence of every station (closest distance to the plot's polygons) are shown in Figure 5. For the present study, the climate data computed in the prediction model described in 3.2.6 follows the same date range (March-October), similar to the approach made regarding remote sensing data.

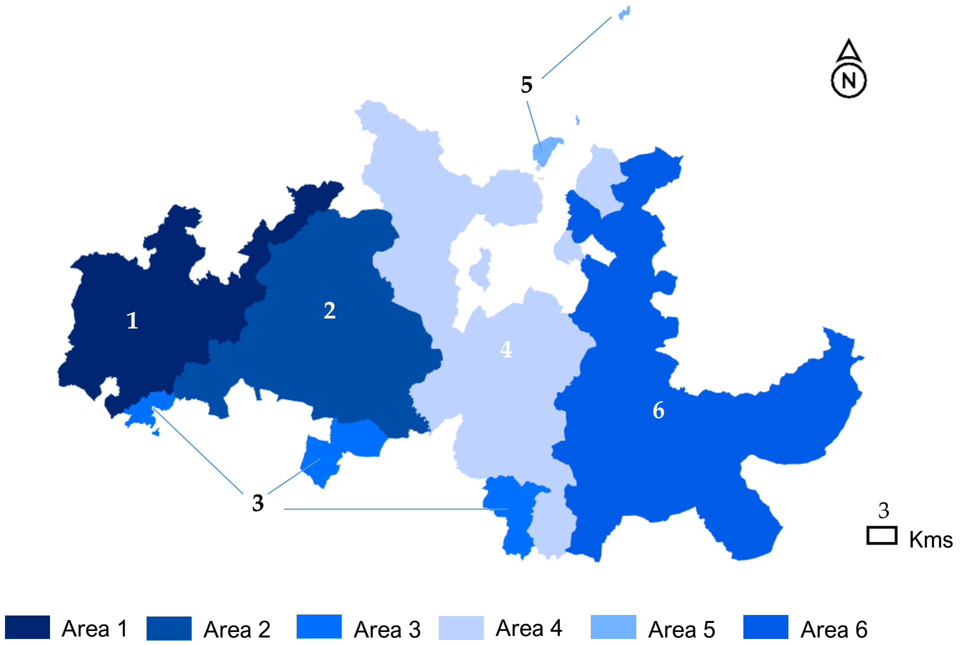

Figure 5 - Considered areas of influence for the six weather stations used in the present study

Table 13 - Descriptive statistics of climate data for the six areas of influence, considering the data from the six automatic weather stations used for the present study (2016-2021) – from March to October

	P (mm)		T (⁰C)		H (%)		W (m/s)		R (KJ/m^2)	
	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd
Area 1	429	152	16.7	4.5	66.0	8.6	1.6	0.3	19813	5878
Area 2	256	110	19.8	4.8	55.3	9.6	1.7	0.3	20251	5045
Area 3	438	187	16.1	4.8	64.3	9.3	2.3	0.4	20062	4283
Area 4	364	181	15.5	4.6	67.1	8.8	1.5	0.3	20025	5489
Area 5	258	110	18.4	5.0	63.1	10.2	2.1	0.4	20255	5213
Area 6	298	108	17.8	5.0	57.5	9.9	2.2	0.4	21125	5371

P (Average annual total precipitation amount - mm); T (Average daily air temperature at 1.5m - ⁰C); H (Average daily relative humidity - %); W (Average daily wind speed – m/s); R (Average daily global radiation – KJ/m^2); sd (standard deviation).

3.2.4 Phenology data

Phenology data was used to define the different timeframes necessary for the model to predict yield as far in advance as possible effectively. The three main grapevine phenological stages are (1) budburst (BUD), which marks the beginning of seasonal grapevine growth and resumed physiological activity after a long period of winter dormancy; (2) flowering (FLO), which is crucial for the reproductive cycle and closely followed by the fruit set stage; and (3) veraison (VER), which initiates the ripening stage, correlated to wine grape quality attributes (Fraga et al., 2016b; Jones and Davis, 2000). The dates for the beginning of each stage were collected from the harvest report generated by ADVID (Association for the Development of Viticulture in the Douro Region - https://www.advid.pt/en) each year (ADVID, 2016, 2017, 2018, 2019, 2020, 2021). The harvest (HAR) start and end dates were collected from the IVDP dataset (Instituto dos Vinhos do Douro e do Porto, I.P. - https://www.ivdp.pt/en) according to the registration of grape entry in the wine-producing facilities (Table 14).

Table 14 - Average start date for the main phenological stages and harvest in the DDR (2016-2021)

Year	BUD	FLO	VER	HAR (start)	HAR (end)
2016	>15 Feb	>15 May	>15 Jul	>18 Aug	<17 Nov
2017	>15 Mar	>15 Apr	>15 Jun	>07 Aug	<21 Nov
2018	>22 Mar	>19 May	>26 Jul	>14 Aug	<15 Nov
2019	>12 Mar	>06 May	>13 Jul	>12 Aug	<15 Nov
2020	>04 Mar	>08 May	>07 Jul	>05 Aug	<18 Nov
2021	>06 Mar	>07 May	>08 Jul	>26 Jul	<16 Nov

BUD (budburst); FLO (flowering); VER (veraison); HAR (harvest)

3.2.5 Yield data

Yield data was provided by IVDP for each parish from 2016 to 2021. The data is collected yearly in grape receptions units scattered along the entire DDR, with the grapes' amount (kg) and origin (parish) recorded for each delivery. The evolution through the different years is aggregated by sub-region and for the entire DDR in Table 15. This same table also shows the average production in kg/ha.

Table 15 - Wine grapes yield in the sub-regions of the DDR (2016-2021)

Year	BC (57 parishes)			CC (64 parishes)			DS (48 parishes)			DDR (169 parishes)		
	Sum	avg	sd	sum	avg	sd	sum	avg	sd	sum	avg	sd
2016	43747	3223	539	79329	3427	806	32430	2969	819	155506	3228	750
2017	57671	4258	1017	76524	3565	1161	34551	3342	816	168746	3736	1088
2018	41828	3197	769	67487	3047	863	33297	3104	803	142611	3114	813
2019	64514	4747	1124	95523	4370	1132	44187	4212	1214	204024	4452	1167
2020	44824	3171	737	73819	3200	931	35129	3194	968	153771	3189	877
2021	55723	4083	957	95896	4233	1148	44167	3846	1149	195787	4073	1092

BC (Baixo Corgo sub-region); CC (Cima Corgo sub-region); DS (Douro Superior sub-region); DDR (Douro Demarcated Region); sum (total annual wine grape production in tons); avg (average annual wine grape production in kg/ha); sd (standard deviation).

3.2.6 Yield prediction model

The system implemented for yield prediction is a Long Short Term Memory (LSTM) Neural Network (Hochreiter and Schmidhuber, 1997) implemented using the Keras framework (https://keras.io/), an open-source software library that provides a Python interface for artificial neural networks, part of TensorFlow library (https://www.tensorflow.org/).

This model was chosen since its architecture is designed to learn long-term dependencies in sequences like time series. The LSTM can process sequences of variables by holding a cell state c_t that carries information across the different time steps of the sequence, receiving minimal updates based on three different gates, namely the forget gate (Equation 2), the input gate (Equation 3), and the output gate (Equation 4).

$$f_t = \sigma\left(W_f \cdot [h_{t-1};\ x_t\ ] + b_f\right) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1};\ x_t] + b_i) \tag{3}$$

$$o_t = \sigma(W_o \cdot [h_{t-1};\ x_t] + b_o\ ) \tag{4}$$

Figure 6 displays the system's architecture. The network receives an input $x_{yp} = [x_t, x_{t+1}, \dots, x_{t+n}]$, a sequence of 49 vectors (sequence length corresponding to the number of observations between March and October), each containing the observed values of every input (NDVI, Rad., Temp., CC, Hum., Prec., Wind – see

Table 19) at a point in time t, for a given year y and parish p.

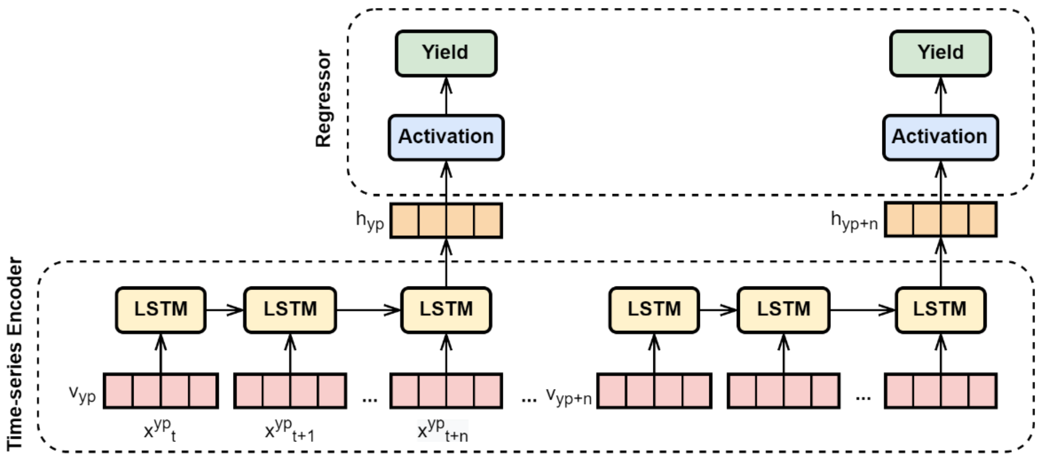

Figure 6 - Yield prediction model overview. The model is divided into two parts: 1) a time-series encoder module that uses an LSTM to generate dense representations; and 2) a regressor

module that receives the last hidden state of the LSTM and calculates the yield volume for a year and location (parish).

This input, together with a cell state c_{t-1} and the hidden state h_{t-1}, of the previous time step t, are passed through the network. The forget gate f_t, a sigmoid layer, takes h_{t-1} and x_t and computes what information should be erased from the previous steps at the current one. Similarly, the input gate i_t, another sigmoid layer, decides what information from the input x_t should be kept. Next, x_t passes a tanh layer that computes new candidate values $\tilde{c}_t$ for the cell state (Equation 5). The cell state c_t is updated by multiplying the old one with the output of the forget gate f_t, and adding the resulting value with the product of the input gate i_t result and the candidate values $\tilde{c}_t$ (Equation 6). This process enables the network to store the information from the current time step and pass it to future steps.

$$\tilde{c}_t = tanh(W_c \cdot [h_{t-1};\ x_t] + b_c\ ) \tag{5}$$

$$c_t\ =\ f_t * c_{t-1} + i_t * \tilde{c}_t \tag{6}$$

Lastly, x_t goes through the output gate o_t. The resulting value is multiplied with the cell state value squashed by a tanh layer (Equation 7).

$$h_t = o_t * tanh(c_t) \tag{7}$$

Through this calculation, we obtain the output value of the network at the current time step h_t. The hidden state of the last time step, h_{yp}, goes through a linear activation layer that computes the Yield Production in Kg/ha for that year y and parish p.

3.3 Results and Discussion

LSTM is one of the most widely used deep learning algorithms in crop yield prediction, along with CNN and Deep Neural Networks (DNN), with temperature, precipitation, and humidity among the most used independent variables (van Klompenburg et al., 2020) to predict yield (dependent variable). This is consistent with the developed model as all three variables are part of the model with the best metrics, with NDVI and wind also as explanatory features (also referenced by T. van Klompenburg, et al.(van Klompenburg et al., 2020) as commonly used for the same purpose).

The average annual wine grape production inter-annual variability can be observed in Table 15 and Figure 7 and is transversal to the different scales of observation, namely DDR, the three subregions (BC, CC and DS), and the 169 parishes. The lowest total production occurred in 2018, with 142,611 tons of grapes for the entire DDR, reaching its peak in the following year

(2019) with a value of 204,024 tons of grapes. The behavior of each sub-region reveals the same tendency registered for the entire DDR either in total aggregated value or production per area unit (kg/ha).

Figure 7 displays the spatial distribution of the average wine grape yield production in kg/ha for each year and each parish. The variability between years and parishes is visible (the values are related to the areas with vineyards and are represented by parish administrative boundaries for easier visualization).

This variability was identified by Cunha et al. (Cunha and Richter, 2011) for the DDR and other regions (Cunha et al., 2010). It can be explained by the spatio-temporal distribution that characterizes agricultural systems as a whole and vineyards in particular, with vulnerability to inter-annual climate variability, especially in the case of our study area, where the vineyards grow under marginal conditions for production with distinctive climatic, topographic and soil characteristics (Gouveia et al., 2011) with temperature and precipitation having a deep connection to yield variability (Camps and Ramos, 2012).

The range between minimum and maximum production per area unit also shows high inter-annual variability, reaching higher values in years when total productivity was higher, namely in 2017, 2019, and 2021.

The spatial autocorrelation was evaluated using Global Moran's I, showing the randomness of the yield data for all years (Table 16).

Table 16 - Spatial autocorrelation assessment (with Global Moran's Index) regarding parish-based wine grape yield in kg/ha (2016-2021)

	Moran's Index	z-score	p-value
2016	-0.003765	0.171343	0.863954
2017	0.017237	1.042057	0.297385
2018	-0.024546	-1.010945	0.312043
2019	-0.022819	-0.833334	0.404656
2020	-0.002469	0.144244	0.885308
2021	-0.005352	0.026708	0.978693

(Spatial relationships: Inverse distance; Distance method: Euclidian; Standardization: Row; Distance threshold: 14187m)

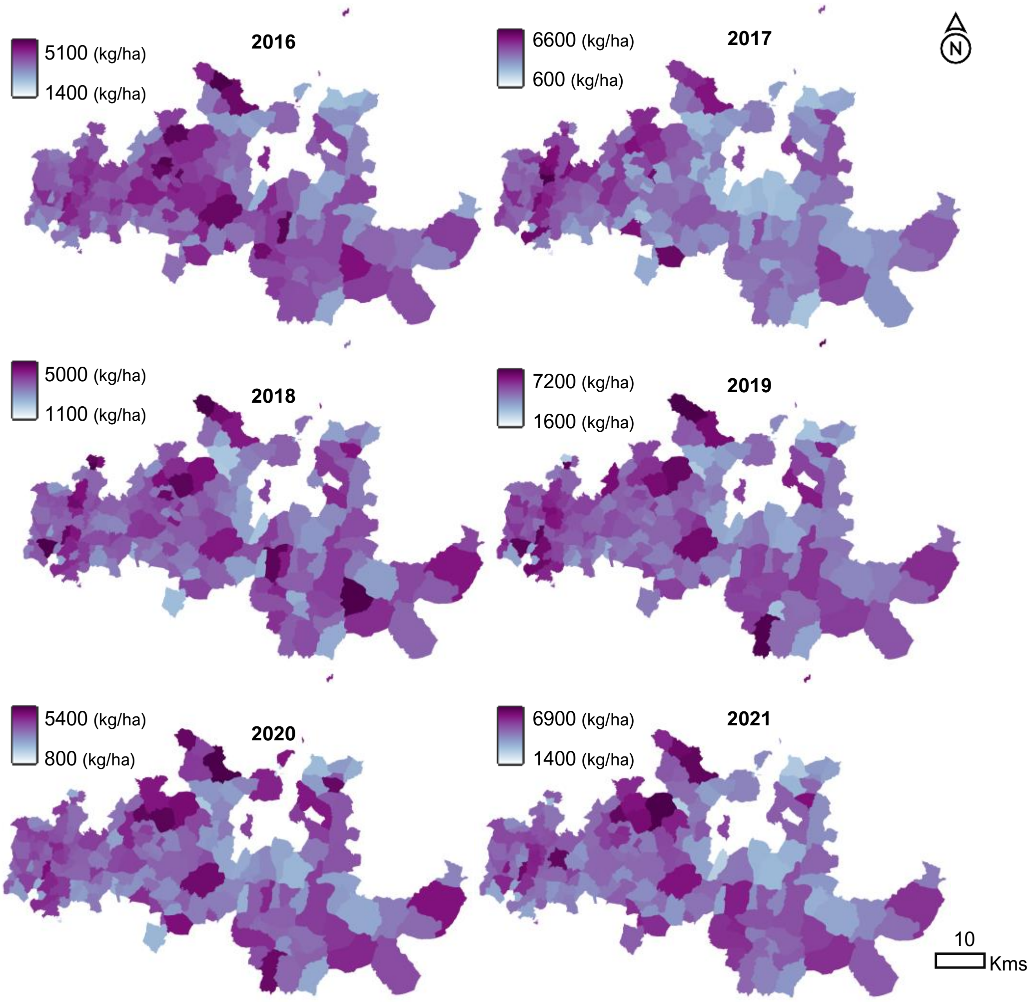

Figure 7 - Spatial distribution of the average Yield Production in kg/ha by year and parish

Calculated NDVI values show a great inter-annual variability throughout the six years between March and October of each year (Table 12), with a strong standard deviation, in the vineyard areas of each parish. Being a region with a low precipitation level, low NDVI values were expected.

The spatial distribution considering the average NDVI values for the period between March and October from vineyard plots represented at the parish level is shown in Figure 8. The identifiable clusters in the different sub-regions, with BC showing higher average values throughout the vegetative cycle, followed by CC and DS with the lower scores, were evaluated using Global Moran's Index, indicating a clustered pattern of the average NDVI values for all years (Table 17). As already mentioned, these values represent the average pixel values inside the areas with vineyards in production in each parish.

Table 17 - Spatial autocorrelation assessment (with Global Moran's Index) regarding parish-based average NDVI (2016-2021)

	Moran's Index	z-score	p-value
2016	0.522983	21.769401	0.000000
2017	0.591388	24.319456	0.000000
2018	0.367304	15.532358	0.000000
2019	0.536924	22.273663	0.000000
2020	0.532426	22.293926	0.000000
2021	0.380097	16.151957	0.000000

(Spatial relationships: Inverse distance; Distance method: Euclidian; Standardization: Row; Distance threshold: 14187m)

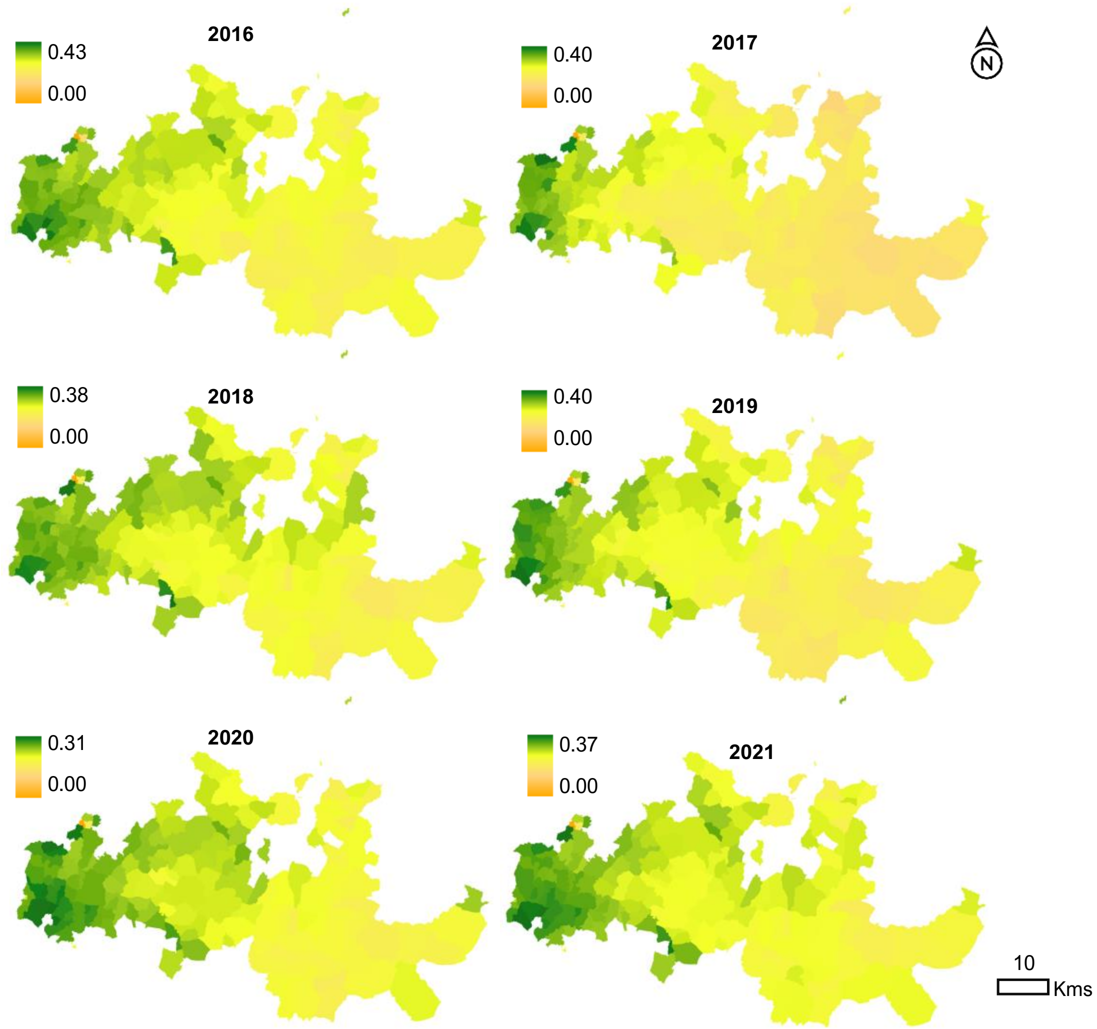

Figure 8 - Spatial distribution of the average NDVI for each year and each parish (March-October)

The NDVI profile over the crop vegetative cycle tends to increment after BUD, reaching its highest values between FLO and VER and decreasing after harvest. This is consistent with the work of several authors (Boulton et al., 1996; Cunha et al., 2010; Gouveia et al., 2011) and associated with the growing period of the vineyards until flowering in May.

Vineyard growth could be restricted in the early stages of the growing season due to the soil water content frequently low at BUD and the lack of winter rainfall (Cunha et al., 2010). The higher average NDVI values demonstrate this in 2016 and 2018, where winter rainfall was more elevated. The highest average NDVI value was recorded on July 9th of 2018, with a 2% cloud coverage value. The effect of cloud coverage is very noticeable, as expected, although the cloud coverage percentage is related to the entire image (to cover the whole DDR spatially, two Sentinel-2 scenes are required). It is usually not noticeable if it concerns areas effectively occupied by vineyards.

Climate plays a fundamental role in the productivity of the vineyard (Fraga et al., 2013; Fraga et al., 2016b) as phenological events and composition are significantly influenced by the climate of preceding months, especially during the growing season (Bock et al., 2011). Weather variables can explain 57.3%, 64.3%, and 57.8% of the variance in yield, sanitary status, and grape composition (Ferrer et al., 2017). According to Gouveia et al.(Gouveia et al., 2011), low rainfall in March positively affects vegetative growth, and high temperatures in late spring are beneficial. This can be seen in the year 2018, where abnormal high precipitation in March accompanied by below-average mean temperatures (Figure 9) was reflected in the production, being the year with the lowest production according to the series considered in the present study (Table 15).

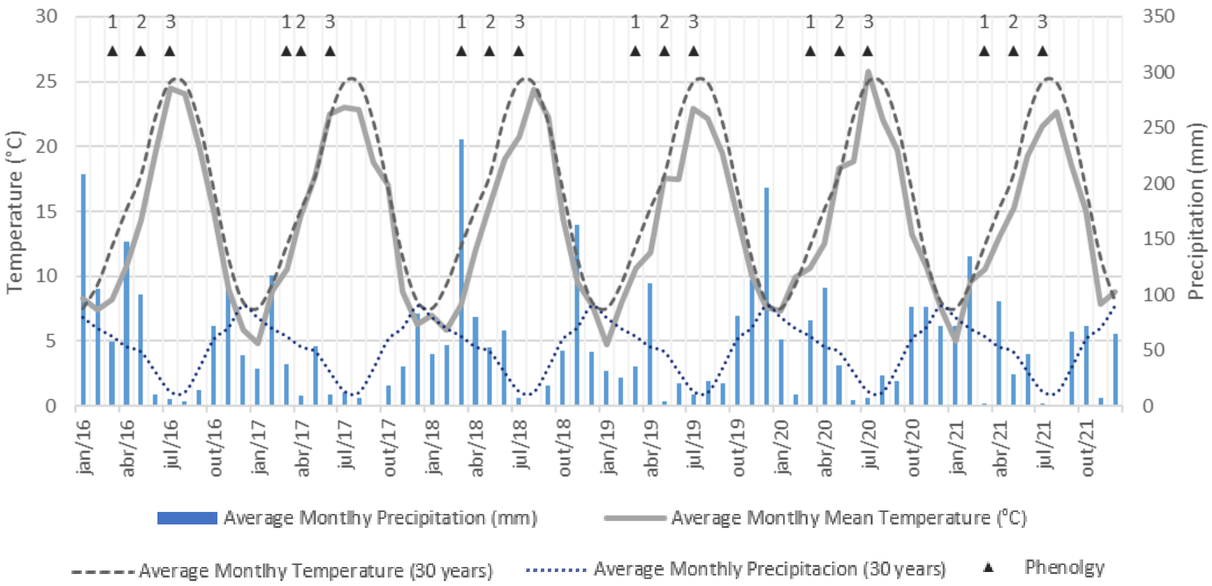

Figure 9 - Average monthly precipitation and mean temperature (2016-2021); Average monthly precipitation and mean temperature (30-year climatological series for 1931-1960 and 1970-2000); Phenology (BUD: 1; FLO: 2; VER:3) for DDR

Although the precipitation throughout the cycle allowed the recovery from water stress that occurred in 2017 (the driest year of the analyzed time range, with lower NDVI values, especially in CC and DS sub-regions, as visible in Figure 8), its volume and timing had a negative impact through an increase in the phytosanitary pressure, scorching and dehydration at a later stage (ADVID, 2018). Precipitation stands out in the years of the present study not only by the high variability between the different areas, months, and years but also from the difference in the available 30-year climatological series (1931-1960 (ADVID, 2016) and 1970-2000 (ADVID, 2021)).

The year 2016 was characterized by a warm and rainy winter, a cold and extremely rainy spring, and very hot and dry summer, contributing to an earlier BUD and a later delay in the previous phenology stages. Intense precipitation in a sensitive phase of the vegetative cycle gave rise to the strong pressure of mildew (ADVID, 2016). Regarding yield, it was the third lowest year of the studied period and below the average of 170,074 tons (-9%) for the entire DDR.

The year 2017, as already stated, was an arid and hot year where the climatic conditions contributed to a significant advance in the vegetative cycle. The prolonged scarcity of precipitation and very high temperatures led to intense hydric and thermal stress at an early stage of the cycle, conditioning the evolution of the vegetation wall and impacting production (ADVID, 2017). Despite that, according to the data provided by IVDP, 2017 had a grape production higher than the one recorded in 2016, but still under the average for the six years (-1%), which can be justified by the quasi-absence of pressure on the phytosanitary aspect.

As already stated, the year with the lowest total production was 2018 (-16% from the average), with a cold and dry winter, cold and extremely rainy spring, and, in its first phase, a cold and rainy summer, and in its second phase, a hot and arid one. Despite the perceived high production potential, climate instability significantly reduced it due to the abnormal harmfulness of the downy mildew (ADVID, 2018).

The years with the highest production were 2019 (+17% from the average) and 2021 (+15% from the average). Both years are characterized by standard dry years with low disease impact (ADVID, 2019, 2021) and are the closest to the 30-year Climatological Normals series. This is also true for the year 2020, although in this case, the spring precipitation led to high pressure regarding the phytosanitary aspect (namely mildew and powdery mildew (ADVID, 2020), which could explain the lower total production (-11% from the average).

Testing for normality through the D'Agostino's (D'AGOSTINO, 1970) and Shapiro-Wilk Test (Shapiro and Wilk, 1965), we concluded that none of the variables was normally distributed, despite some of them, namely Yield Production, Temperature, and Relative Humidity, showing a Gaussian pattern. We calculated the Pearson correlation to assess how the different explanatory variables are related (Table 18).

Table 18 - Pearson correlation between the variables used for Yield Prediction.

Pearson Correlation	NDVI	R	T	W	P	H	CC
NDVI	1.00						
Radiation	0.75	1.00					
Temperature	0.47	0.61	1.00				
Wind	-0.19	-0.07	-0.28	1.00			
Precipitation	-0.51	-0.49	-0.36	0.36	1.00		
Humidity	-0.61	-0.65	-0.61	0.07	0.49	1.00	
Cloud Coverage	-0.87	-0.66	-0.43	0.11	0.38	0.65	1.00

NDVI (Normalized Difference Vegetation Index); R (Global radiation); T (Air temperature); W (Wind speed); P (Precipitation); H (Relative humidity); CC (Cloud Coverage)

NDVI presents a negative correlation of -0.87 with Cloud Coverage, -0.61 with Humidity, -0.51 with Precipitation and -0.19 with Wind Intensity. On the other hand, NDVI has a positive correlation of 0.75 with radiation and 0.47 with Temperature. The polarity of the correlations provides a clear distinction between variables that exhibit a similar pattern to NDVI, namely Radiation, and variables that present almost an opposite behavior, namely Cloud Coverage and Humidity. It is also possible to conclude that radiation values vary inversely to Cloud Coverage and Humidity.

3.3.1 Yield prediction model optimization

Yield prediction was evaluated for the period between March and October by performing a random training/test split, leaving 80% of the observations to train the model and 20% to test it. The metrics used to evaluate the prediction performance were the MAE and the MSE. The different number of LSTM layers and 8, 16, 32, 64, and 128 hidden units were tested during the training setup. We also introduced a dropout layer with different values and experimented with different learning optimization methods and rates. Ultimately, a small model with only one layer and 16 hidden units, no dropout, using the Adam optimizer (Kingma and Ba, 2014) and a fixed learning rate of 0.001, yielded the best performances (execution environment: GPU; Loss Function: MSE). Moreover, to understand the impact of each input variable on the yield prediction performance and find the best combination of variables, we ran a stepwise backward feature selection process, in which we started by evaluating the model using all variables as input and gradually removing one at the time, based on their correlation with NDVI (higher absolute correlations were removed first). Table 19 summarizes these experiments.

Table 19 - Evaluation of Yield prediction model through a stepwise backward feature selection process. Best metrics highlighted.

Step	Variables	MAE (kg/ha)	MSE (kg/ha)
1. All variables	NDVI, Rad., Temp., CC, Hum., Prec., Wind	688.29	83.77
2. Remove Cloud Coverage	NDVI, Rad., Temp., Hum., Prec., Wind	678.84	81.80
3. Remove Radiation	NDVI, Temp., Hum., Prec., Wind	**672.55**	**81.30**
4. Remove Relative Humidity	NDVI, Temp., Prec., Wind	685.28	82.80
5. Remove Precipitation	NDVI, Temp., Wind. **(+) Hum.**	680.05	82.64
6. Remove Temp	NDVI, Hum., Wind., **(+) Prec.**	698.93	83.73
7. Remove Wind	NDVI, Hum., Prec., **(+) Temp.**	823.49	106.85
8. Only NDVI	NDVI	766.59	99.24

In the scenario in which the model's performance increases or remains the same after removing a variable, we excluded the variable for the next tests. Alternatively, the variable would be added in the following experiment if the performance decreased. We also ran the model considering only NDVI as input (step 8). The optimal combination of input features, with an MAE of 672.55 and an MSE of 81.30, considered NDVI, Temperature, Relative Humidity, Precipitation, and Wind Intensity (step 3). The removed variables in the best model, Radiation, and Cloud Coverage, were the ones with the highest correlation with NDVI (see Table 18). This was expected since their explanatory power is already expressed in NDVI. On the other hand, the most significant drop in model performance seems to be when removing the feature Wind, the one with the lowest correlation with NDVI. Wind influence can be negative (e.g., physiological effects of photosynthesis disruption, breaking off new shoots, increasing evapotranspiration) and positive (e.g., reduced disease infestations, limiting the occurrence of radiation frosts) on vine health and yield. The data referring to this variable shows high interannual variability between areas of influence, where areas 3 and 6 stand out with consistently higher values than the other areas. Also, it is worth noting that the model using only NDVI as a feature for yield prediction achieves higher performance than the one using NDVI, Humidity, Precipitation, and Temperature.

3.3.2 Yield prediction model analysis

The model with the best metrics was run to analyze in more detail its prediction performance. The prediction was made for each year, using it as the test set, while all other years were used as input to train the model. We considered two different moments in time, corresponding to

FLO (May) and VER (July) phenology stages, considering the main characteristics of vineyards at DDR (Table 14).

The model's performance at the FLO stage is considered very poor with an average absolute prediction error for the entire DDR between 2016 and 2021 of 38% against the 17% average error achieved when the same model is run at the VER stage. This error represents the deviation regarding kg/ha from the actual average of wine grapes collected.

Analyzing each year for the entire DDR and the different sub-regions at the FLO stage (Table 20), the best prediction was made in 2021 for the whole DDR, with the model underestimating the yield per hectare at 25% and 19% for the DS sub-region. In 2016, we can see the most significant difference between predictions in sub-regions, with DS showing almost twice the error as CC. The worst performances are for 2017, an arid year, and 2019, the year with the highest productivity per hectare compared to the other years.

Table 20 - Prediction for the DDR and sub-regions made at the FLO stage

Year	Region	AVG	PRED	DIF	DIF_abs	DIF_%	DIF_abs_%
2016	DDR	3228	4196	968	968	30	30
	BC	3223	4157	934	934	29	29
	CC	3427	4194	767	767	22	22
	DS	2969	4245	1276	1276	43	43
2017	DDR	3736	1873	-1863	1863	-50	50
	BC	4258	1921	-2337	2337	-55	55
	CC	3565	1865	-1700	1700	-48	48
	DS	3342	1827	-1515	1515	-45	45
2018	DDR	3114	4124	1010	1010	32	32
	BC	3197	4286	1089	1089	34	34
	CC	3047	3983	937	937	31	31
	DS	3104	4118	1013	1013	33	33
2019	DDR	4452	1779	-2673	2673	-60	60
	BC	4747	1711	-3036	3036	-64	64
	CC	4370	1751	-2619	2619	-60	60
	DS	4212	1897	-2315	2315	-55	55
2020	DDR	3189	4127	939	939	29	29
	BC	3171	4110	939	939	30	30
	CC	3200	4121	920	920	29	29
	DS	3194	4156	962	962	30	30
2021	DDR	4073	3071	-1001	1001	-25	25
	BC	4083	2999	-1084	1084	-27	27
	CC	4233	3090	-1143	1143	-27	27
	DS	3846	3132	-714	714	-19	19

BC (Baixo Corgo sub-region); CC (Cima Corgo sub-region); DS (Douro Superior sub-region); DDR (Douro Demarcated Region); AVG (Real wine grape production average in kg/ha); PRED (Estimated wine grape production in kg/ha); DIF (PRED-AVG in kg/ha); DIF_abs (DIF in absolute value); DIF_% (PRED-AVG in %); DIF_abs (DIF_% in absolute value)

The results mainly improved at the VER stage (Table 21) and didn't follow the same FLO estimation pattern. The best prediction was made in 2020 for the whole DDR, with the model overestimating the yield per hectare at 8% and 6% for CC and DS sub-regions, respectively, followed by the results for 2019. These years are less deviant from normal climate variables, despite having the higher production (in 2019) and the second lower production (in 2020). This is also true for 2021, but with a worst prediction. The biggest difference between predictions in sub-regions is in 2017, with CC and DS having almost triple of error value as BC, in 2020 where the error in BC doubles the one in the other sub-regions. The worst performances are for 2016, with the model underestimating yield, characterized by climate conditions that favored phytosanitary problems, and in 2017, especially arid in CC and DS sub-regions.

Table 21 - Prediction for the DDR and sub-regions made at VER stage

Year	Region	AVG	PRED	DIF	DIF_abs	DIF_%	DIF_abs_%
2016	DDR	3228	2459	-769	769	-24	24
	BC	3223	2454	-769	769	-24	24
	CC	3427	2460	-967	967	-28	28
	DS	2969	2463	-505	505	-17	17
2017	DDR	3736	4441	706	706	19	19
	BC	4258	4605	347	347	8	8
	CC	3565	4392	826	826	23	23
	DS	3342	4312	970	970	29	29
2018	DDR	3114	3621	507	507	16	16
	BC	3197	3730	533	533	17	17
	CC	3047	3552	505	505	17	17
	DS	3104	3583	479	479	15	15
2019	DDR	4452	3827	-625	625	-14	14
	BC	4747	4000	-747	747	-16	16
	CC	4370	3737	-633	633	-14	14
	DS	4212	3741	-470	470	-11	11
2020	DDR	3189	3446	257	257	8	8
	BC	3171	3549	378	378	12	12
	CC	3200	3399	198	198	6	6
	DS	3194	3385	191	191	6	6
2021	DDR	4073	3312	-761	761	-19	19
	BC	4083	3226	-857	857	-21	21
	CC	4233	3373	-860	860	-20	20
	DS	3846	3333	-513	513	-13	13

BC (Baixo Corgo sub-region); CC (Cima Corgo sub-region); DS (Douro Superior sub-region); DDR (Douro Demarcated Region); AVG (Real wine grape production average in kg/ha); PRED (Estimated wine grape production in kg/ha); DIF (PRED-AVG in kg/ha); DIF_abs (DIF in absolute value); DIF_% (PRED-AVG in %); DIF_abs (DIF_% in absolute value).

Table 22 illustrates the descriptive statistics at parish level. Furthermore, Figure 10 shows the spatial distribution by parish of the average absolute errors for the six-year analyzed period. The model's overall performance at the parish level is considered poor, not only regarding the error but also the high inconsistency when we look at individual parishes and the error behavior for each year.

Between the two stages, it is clear that also at the parish level, the model works better at VER stage, although in 36% of the parishes the error is lower if the model is run in the FLO stage, with an average difference of 10%, being the lowest 2% and the highest 23%

Table 22 - Descriptive statistics for average absolute error in each parish (2016-2021)

	avg	sd	median	min	max
2016	0.26	0.14	0.27	0.00	0.80
2017	0.38	0.58	0.22	0.00	6.55
2018	0.32	0.36	0.22	0.00	2.21
2019	0.24	0.21	0.20	0.00	1.51
2020	0.29	0.38	0.18	0.00	3.11
2021	0.26	0.23	0.22	0.00	2.10

avg (Parish average absolute error); sd (standard deviation); median (Parish average median absolute error); min (Parish average minimum absolute error); max (Parish average maximum absolute error)

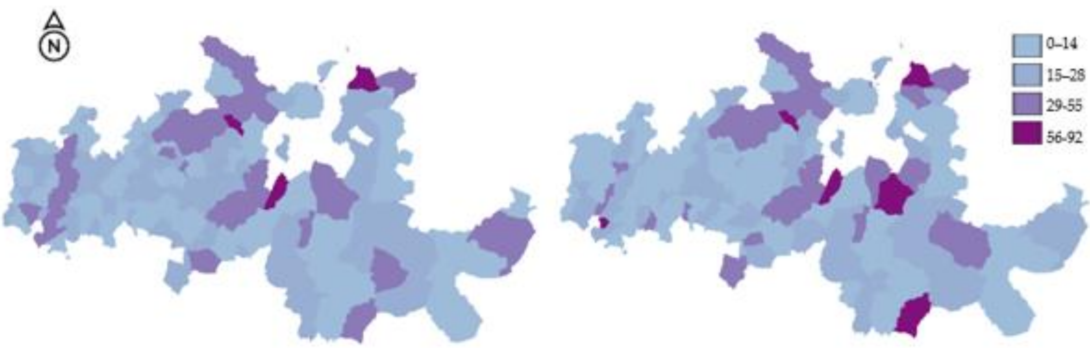

Figure 10 - Spatial distribution of the average absolute error (%) in each parish for the period 2016-2021 at FLO (left) and VER (right)

3.3.3 Comparative study and discussion

To further evaluate our model, we conducted a comparative study regarding other alternatives for regional vineyard yield estimation (Table 23). A more in-depth comparison was made considering the model currently used in the study area by the local authorities.

Table 23 - Different methodological approaches for regional vineyard yield prediction (Barriguinha et al., 2021)

Reference	Methodological Approach	Data Sources	Test environment	Related Variables	Estimation
(Cristofolini and Gottardini, 2000)	Pollen Based	Hirst type sampler volumetric spore trap (Lanzoni VPPS-2000)	In-field	Airborne pollen concentration	R^2=0,92 (for grape production)
(Fernandez-Gonzalez et al., 2011)	Pollen Based	Aerobiological data (Lanzoni VPPS-2000 volumetric trap)	In-field	Meteorological and phytopathological variables	R^2=0,98 (for yield)

(Fernández-González et al., 2020)	Pollen Based	Pollen Hirst volumetric sampler and Cour passive trap	In-field	Airborne pollen concentration, weather data	R^2=0,96 (Cour); R^2=0,99 (Hirst)
(Besselat, 1987)	Pollen Based	Pollen concentration data	In-field	Airborne pollen concentration	R^2<0,98 (for yield)
(Cunha et al., 2015)	Pollen Based	Airborne pollen trap	Simulated	Airborne pollen concentration	0,71<R^2<0,86 (for annual wine production)
(Cunha et al., 1999)	Pollen Based	Pollen concentration data	In-field	Airborne pollen concentration	R^2=0,93 (for yield)
(Cunha et al., 2003)	Pollen Based	One Cour Pollen Trap	In-field	Airborne pollen concentration	0,66<R^2<0,99 (for wine production)
(González-Fernández et al., 2020)	Pollen Based	Aerobiological data (Lanzoni VPPS-2000 volumetric sampler), Meteorogical data	In-field	Airborne pollen concentration and Meteorologic data	R^2=0,99 (for yield)
(Gouveia et al., 2011)	Vegetation Indices	Corine Land Cover map, wine statistics, monthly means of climate variables and NDVI	Simulated	tmax, tmin, tavg, prec, NDVI	0,62<R<0,90 (for wine production)
(Sun et al., 2017)	Vegetation Indices	Satellite-based (NDVI) and (LAI)	In-field	NDVI, LAI	0,66<R<0,83 (for NDVI and Yield) and 0,66<R<0,83 (for LAI and Yield)
(Cunha et al., 2010)	Vegetation Indices	Satellite data from vegetation (NDVI from SPOT)	In-field	NDVI	0,73<R^2<0,84 (for yield)
(Cola et al., 2014)	Crop Simulation Model	Weather data and plant characteristics	Simulated/In-field Validation	Weather data and plant characteristics	R^2=0,96 (for yield in low-density canopies) R^2=0,94 (for yield in high-density canopies)
(Fraga et al., 2015)	Crop Simulation Model	Climate, soil, and management practices	Simulated/In-field Validation	Climate data, soil and terrain parameters, water stress indices, management practices	R^2=0,86 (for yield)
(Valdes-Gomez et al., 2009)	Crop Simulation Model	Phenology and harvest date, Soil water content, water stress, and grapevine growth and yield	Simulated/In-field Validation	Phenology and harvest date, soil water content, water stress, and grapevine growth and yield	R^2=0,85 (for yield)
(Sirsat et al., 2019)	Crop Simulation Model	Weather, yield, phenological dates, fertilizer information, soil analysis, and maturation index data	Simulated/In-field Validation	Weather, phenological dates, fertilizer information, soil analysis, and maturation index data	24,2%<RRMSE<28,6%
(Fraga and Santos, 2017b)	Other Models	Daily historic meteorological conditions, yield data	In-field	Temperature and Precipitation	0,68 ≤ r ≤ 0,84 (for grapevine production)
(Santos et al., 2020a)	Other Models	Monthly mean air temperatures and monthly total precipitation data	In-field	Monthly mean air temperatures and monthly total precipitation	Wine production classes (1-low, 2-normal, 3-high): average estimation ratio of 79%(calibration) 67%(validation)

Comparing our results with the works of Cunha et al. (Cunha et al., 2003; Cunha et al., 1999), that developed and used an estimation model in the same study area (DDR) and relied on the relationship between airborne pollen and yield (Table 24), we can state that our results are very satisfactory. The pollen-based model predicts wine production for the whole DDR with a minimum and maximum threshold, and ADVID has used it since 1992 with the predictions made yearly at the VER stage. To compare both errors, we considered the average absolute error and a conversion factor of 750kg of grape for 550 liters of wine (average based on the IVDP data set for the six years).

Table 24 - Prediction for the DDR based on pollen model made at the VER stage (prediction data from ADVID reports (ADVID, 2016, 2017, 2018, 2019, 2020, 2021))

Year	PROD	PRED (min)	DIF (min)	DIF (min) (%)	PRED (max)	DIF (max)	DIF (max) (%)	PRED (avg)	DIF (avg)	DIF (avg) (%)
2016	158677	143727	-14950	-9%	158318	-359	0%	151023	-7654	-5
2017	171413	199500	28087	16%	215864	44450	26%	207682	36269	21
2018	145282	190636	45355	31%	204955	59673	41%	197795	52514	36
2019	207900	197318	-10582	-5%	216273	8373	4%	206795	-1104	-1
2020	153940	148364	-5576	-4%	168136	14197	9%	158250	4310	3
2021	195802	176455	-19347	-10%	191045	-4756	-2%	183750	-12052	-6

DDR (Douro Demarcated Region); PROD (wine grape production for the entire DDR in tons/year); PRED(min) (minimum estimated wine grape production in tons/year considering a conversion factor of 750kg of grape for 550 liters of wine); PRED(max) (maximum estimated wine grape production in tons/year considering a conversion factor of 750kg of grape for 550 liters of wine); PRED(avg) (average estimated wine grape production in tons/year considering a conversion factor of 750kg of grape for 550 liters of wine); DIF(min) (PRED(min)-PROD in kg/year); DIF(min)(%) (PRED(min)-PROD in %); DIF(max) (PRED(max)-PROD in kg/year); DIF(max)(%) (PRED(max)-PROD in %); DIF(avg) (PRED(avg)-PROD in kg/year); DIF(avg)(%) (PRED(avg)-PROD in %).

Since the pollen model only estimates the whole DDR, the comparison was only made considering that at the VER stage. According to the authors, both models can obtain very good results. In the study's time frame, the pollen model achieved a lower average error for the years 2016 and 2019 to 2021 and a worse result for the years 2017 and 2018. Considering the average differential for the pollen model, both models coincide in the years in terms of underestimation and overestimation yield. The worst performance could be attributed in 2017 due to early flowering and in 2018 due to significant variation in water stress as discussed by the authors, stating that additional parameters, such as disease occurrence, agronomic, and weather conditions after flowering are required (Cunha et al., 2003).

The model developed in the present study can deliver prediction at a sub-regional level. Implementing the pollen model would require a more comprehensive network of pollen traps with cost implications. Furthermore, developing a model estimating grape yield in kg/ha and not in wine production can be seen as an advantage for being more comprehensive for the different actors in the DDR and for other regions where the regulations are not so specific and focused on the Port wine.

The current model also performs well when referring to other pollen-based models (and without the limitations mentioned above) with estimations in line with the work of Cunha et al., (Cunha et al., 2003; Cunha et al., 1999; Cunha et al., 2015) for the DDR. The different studies for regional-scale applications identified in the authors' previous work (Barriguinha et al., 2021) have an overall average R^2 between 0,71 and 0,99. Cristofolini et al. (Cristofolini and Gottardini, 2000) determination of the pollen index between the days when 5 and 95% of the season's total pollen concentration were found achieved very good results, similarly to the work of Besselat (Besselat, 1987). With a different approach, Gonzaléz et al. (González-Fernández et al., 2020) and Fernandez et al. (Fernández-González et al., 2011; Fernández-González et al., 2020; Fernandez-Gonzalez et al., 2011) combined aerobiological, phenological, and meteorological data achieving equally accurate production estimations more than one or two months in advance.

Compared with other models based on vegetation indices applied to vineyard yield estimation at the regional level, the current model also performs well. Gouveia et al. (Gouveia et al., 2011) worked on multi-linear regression models using Corine Land Cover, wine statistics, NDVI, and meteorological variables (monthly averages of maximum, minimum, and daily mean temperature and precipitation) to estimate yield with $0,62<R^2<0,90$ in a simulated test environment. Using Satellite Pour l'Observation de la Terre (SPOT) ten-day synthesis vegetation product (S10) Cunha et al. (Cunha et al., 2010) based on a correlation matrix between the wine yield of a current year and the full set of 10-day synthesis NDVI also achieved good results ($0,73<R^2<0,84$). Sun et al. (Sun et al., 2017) combined satellite-based NDVI from Landsat and MODIS with LAI obtained using a Li-Cor LAI-2000 instrument with good results, $0,66<R<0,83$ (for NDVI and Yield) and $0,66<R<0,83$ (for LAI and Yield) although the validation was made locally in a small area.

At the regional scale, crop simulation models are also an alternative for vineyard yield estimation (Barriguinha et al., 2021). This approach allows virtual experiments that can be made, for example, at specific phenological stages for testing hypotheses that could take years under real field conditions, with the added capability of integrating the findings in decision support systems (DSS). Cola et al. (Cola et al., 2014) achieved good results simulating the fruit load based on light interception derived gross assimilation and thermal and water limitations with $R^2=0,96$ (for yield in low-density canopies) and $R^2=0,94$ (for yield in high-density canopies). Sirsat et al. (Sirsat et al., 2019) focused on grape yield predictive models for flowering, coloring, and harvest phenostages using ML techniques and climatic conditions, yield, phenological dates, fertilizer data, soil analysis, and maturation index data to construct the relational dataset. The authors identified dew point, relative humidity, and air temperature as the most favorable variables in building the model, with $24,2\%<RRMSE<28,6\%$ for yield estimation. Fraga et al. (Fraga et al., 2015) and Valdes et a. (Valdes-Gomez et al., 2009) used a similar approach using STICS models with $R^2=0,86$ and $R^2=0,85$ respectively both with overestimation and underestimation, depending on the regions. In terms of performance, the current model can perform as well as the crop simulation alternatives. Those are much more complex as they are not limited to yield and simulate plant growth and development. They need to be calibrated and validated, requiring adaptability for new environments (distinct climate, soil, varieties, and management), making operationality and transferability difficult, complex, and costly in terms of time and biophysical data requirements (Sirsat et al., 2019).

The current model outperforms other models, such as the simple grape production model (PGP) based on favorable meteorological conditions, developed by Fraga et al. (Fraga and Santos, 2017b), and the empirical model proposed by Santos et al. (Santos et al., 2020a) where temperature and precipitation averaged over different periods, along with the anomalies of wine production in the previous five years, were used as predictors.

Models based on computer vision and image processing (by extraction of variables that can be related to the actual yield: number of berries, bunch/cluster area, leaf area, number of flowers, stems, and branches), trellis tension, laser, radar, and radio frequency data processing also constitute viable approaches for estimating vineyard yield. Nevertheless, those are not suitable for regional-scale implementation. Apart from the trellis tension approach, the real applicability under field conditions in commercial vineyards is not referenced for the most part (Barriguinha et al., 2021).

3.4 Conclusions

The use of LSTM neural network can be applied to vineyard yield prediction at the regional scale. It can perform as well as the other identified methodologies, outperforming some of them while dealing with some of the above-mentioned limitations. This and other ML-based methods can help study complex interactions between biotic and abiotic systems to understand and make predictions (Thessen, 2016), as in the current study.

The developed model allows for an early yield estimation with better results at the VER stage (one month before harvest start) when compared to the FLO stage (3 months before harvest start), with an absolute error for the whole study region between 8% and 24%, and between 6% and 29% for the sub-regions. The estimation range is much broader regarding estimations made at higher spatial resolution (parish level). Although 68% of the parishes have an average error below 20%, we consider that the model is not yet capable of predicting at that more detailed scale.

Despite the good results, the fact that there are no production data at the plot level (limiting the size of the dataset), a short time series of yield data, and a low number of weather stations (limiting the size and quality of the dataset considering the size and characteristics of the study area), are factors perceived as sources of error and limitations for the current model, and the reason for not being able to go further for larger scales. This is consistent with the limitations identified for this type of model applied to yield prediction (van Klompenburg et al., 2020).

Being a prediction model, this DL approach falls short of interpretability and, unlike more common inferential models, is a black-box model for making predictions (Emmert-Streib et al., 2020).

The variability and randomness of the yield and the different explanatory variables used between seasons, sub-regions, and parishes make the challenge of rapidly estimating yield very complex (Cunha et al., 2010). For the present study, we concluded that using NDVI alone is insufficient for a robust and accurate model developed with this methodology. As climatic variables have a strong correlation to yield (Badr et al., 2018; Ferrer et al., 2017), using satellite data and meteorological variables constitutes a better strategy for regional scale estimation of wine production (Gouveia et al., 2011). The performance is also very dependent on environmental conditions and management strategies (Sun et al., 2017), with yield correlated with an extensive list of climate, soil, and plant variables with high temporal and spatial heterogeneity. Also, the relation to quality is one of the biases that yield estimation needs to deal with, as the producer's management decision directly impacts quality and yield.

The integration of more specific multispectral based VI data, such as Leaf Area Index (LAI), or the use of Synthetic Aperture Radar (SAR) and Light Detection And Ranging (LIDAR) data can be tested as potential future developments in this field.

4. Final Considerations

4.1 Summary of findings

To date, the alternative methodologies for yield estimation, as demonstrated in the first study, surpass the limitations assigned to traditional manual sampling methods with the same or better results on accuracy. They all have advantages and shortcomings, but they still lack a fundamental key aspect: the real application in commercial vineyards. Despite extensive research in this area, adoption at an operational level to effectively substitute the manual sampling estimation is residual. Methods made available to winegrowers to estimate production as far in advance as possible must be simple and with little data, preferably with data that producers can access quickly, easily, and cheaply and, if possible, without the need for intensive training or validation. The best approach must consider the availability and/or possibility of having the required inputs (required data is sometimes not available), the adequate spatial resolution (field level or regional level), the necessary granularity (information regarding the spatial variability in each area) and required precision (e.g., a simple smartphone camera, despite the loss in quality, can be in many cases a cost-effective alternative to hyper and multispectral cameras, LiDAR, ultrasonic and radar sensors).

The synergistic use of proximal and remote sensing with AI can be one of the best ways to model a vineyard production system. Still, due to its inherent complexity, it is a difficult challenge to apply because of the diversity of field conditions, as remote sensing data is dependent on spatial, temporal, and spectral resolution; and yield is correlated with an extensive list of climate, soil and plant variables that have high temporal and spatial heterogeneity. Also, the relation to quality is one of the biases that yield estimation needs to deal with, as the producer's management decision directly impacts quality and yield.

For local estimation at the farm level, data-driven models based on computer vision and image processing are the ones the researcher's community is putting more effort into and can be classified as the easiest to deploy by growers under real field conditions. Data acquisition can be made easily on the go with a vast array of solutions ranging from a simple smartphone to an autonomous robot platform, a UAV, or even agriculture equipment. Despite promising results in estimating yield, these methods are not fully matured yet. Management practices (e.g., trellis, leaf-pulling, shoot/cluster thinning, and shoot positioning) can directly impact data acquisition by affecting the relationship between what is measured and the predicted yield. There are still problems with occlusion, algorithms are generally variety-dependent, and environmental dynamics are challenging. Data acquisition speed, computational processing constraints, and the availability of predictive yield maps as output should be addressed in commercial applications. Vegetation indices are also a good alternative as they can be easy to deploy and used at different scales with good results, especially NDVI. Data acquisition is generally feasible and affordable, but transforming data into usable information requires technical knowledge not often available to all farmers. The past limitations linked to the direct use of multispectral satellite remote sensing data, such as insufficient spatial resolution, inadequate temporal resolution, and complex data access and processing, were significantly overcome since the launch in mid-2015 of the EU Copernicus Program' Sentinel-2 mission combined with the development of appropriate desktop and cloud-based data processing platforms (e.g., Google Earth Engine: https://earthengine.google.com/; Sen2-Agri: http://www.esa-sen2agri.org/; and Sen4CAP: http://esa-sen4cap.org/. As for models based on computer vision and image processing, correspondent operational solutions are not yet available for growers as needed. Future commercial solutions can pass by including yield estimation algorithms in UAVs data management software or web platforms like EO Browser (https://apps.sentinel-hub.com/eo-browser/) or EOS Platform (https://crop-monitoring.eos.com/) providing multispectral satellite data and derived products and indices, with required parametrization when needed. Crop models were also referenced as one of the best alternatives for estimating yield. Still, few examples were identified, mainly because of the complexity of their development, especially hard in vineyards because of the inherent specificities and the required data for calibration in different locations and for different varieties. Other more residual approaches like laser, radar, radio frequency, and ultrasonic data can provide new alternatives to cope with some of the difficulties encountered, especially in computer vision and image processing approaches.

As demonstrated in the first study, there is a lack of solutions for estimating yield at broader scales (e.g., regional level). The perception is that decisions are more likely to take place on a smaller scale, which in some cases, is inaccurate. It might be the case in regulated areas (82,4% of vines in the EU are dedicated to the production of 'quality wines' planted for wines under the Protected Designation of Origin (PDO) and Protected Geographical Indication (PGI) classification) and areas where support for small viticulturists is needed and made by institutions with proper resources and a large area of influence. This is corroborated by the fact that data-driven models based on Trellis Tension and Pollen traps are being used for yield estimation at regional scales in real environments in different regions of the world. The main disadvantages/difficulties of using pollen-based models are: choosing the best placement for sampling devices to represent spatial variability effectively; the number of observations for model calibration (historical data not commonly available); costly and complex laboratory processes; plant dynamics (high variations of the area with vineyards around the pollen traps); temperature and precipitation variations; vineyard management activities (fertilization impact);

and identification of the beginning and final of the pollen season. As for Trellis Tension models, despite the better estimative that can be achieved and the ability to monitor near to real-time, the applicability of this method to commercial vineyards still needs to be evaluated regarding needed calibration for different vineyards and trellis systems, consistency across seasons, installation costs, number of sensors and spatial deployment.

In recent years, DL has been considered a breakthrough technology in ML and DM, including in the RS research field. ML methods are increasingly being used as a tool for crop yield prediction, with LSTM and CNN being the most widely used DL approaches, with better results when compared to traditional ML approaches for crop yield prediction, taking advantage of the ability to extract features from available data. Despite being recent, this ANN-based data science approach is not new to vineyard yield estimation. It is leading the alternative methods as one of the most utilized techniques for attempting an early yield estimation. However, it has been limited to small-scale experiments, mostly in controlled environments associated with models based on computer vision and image processing. Despite its use in remote and proximal sensing models with an inherent spatial component, predictive yield maps are scarcely referenced and used as an output of yield estimation models. New approaches like GeoAI are not yet referred to in the literature. As spatial variability and heterogeneity are some of the more critical parameters for decision-making in PV (the producer wants to know the quantity and where that quantity is), it is a relevant research gap that is addressed in the second study with the use of LSTM neural network yield estimation model with remote sensing (satellite-based time-series of NDVI calculated from Sentinel 2 images) and climate data (local automatic weather stations) applied to vineyard yield prediction at the regional scale. It can perform as well as the other identified methodologies, outperforming some while dealing with some of the limitations mentioned above. This and other ML-based methods can help study complex interactions between biotic and abiotic systems to understand and make predictions, as in the current study.

The developed model allows for an early yield estimation with better results at the VER stage (one month before harvest start) compared to the FLO stage (3 months before harvest start) and can be applied at different scales. The variability and randomness of the yield and the different explanatory variables used between seasons make the challenge of rapidly estimating yield very complex. Using NDVI alone is insufficient for a robust and accurate model developed with this methodology. As climatic variables have a strong correlation to yield, satellite data and meteorological variables constitute a better strategy for regional scale estimation of wine grape production.

4.2 Contributions

The research approaches for predicting yield in vineyards for wine production have the potential and can, for the most, serve as an alternative to traditional estimation methods based on manual sampling, with better results, but they lack practical applicability under field conditions in commercial vineyards. Choosing the right approach and ensuring the applicability under field conditions depends on the availability of data at the adequate spatial and temporal resolution for the required accuracy and precision of the estimation in a cost-effective model capable of justifying the advantage of knowing in advance the quatity of grapes in a given area.

The proposed model using NDVI and climate data with a DL approach based on an LSTM Neural Network can produce an adequate estimation of wine grape yield up to 1-2 months before harvest. To the best of the author's knowledge, it is the first application of DL to regional vineyard yield estimation.

The developed estimation model can cope with the limitations identified in the current model in use in the study area, which relies on the relationship between airborne pollen and wine production, namely: predicting only for the entire region, predicting wine production instead of wine grape production; the need to maintain representative pollen sampling devices with high maintenance and operational costs, and complex laboratory process to treat the data; and a wide prediction interval.

The developed model can be transferred to other regions, giving decision-makers at different levels a good estimation, not only for the total regional and sub-regional wine grape production areas but also at a more detailed scale (depending on the granularity of the available datasets).

4.3 Limitations and future research

Despite the good results, at the regional level, aggregated production data limits the size and quality of the dataset with an impact on the model accuracy, constituting a limitation to go further for larger scales (parcel level) with good results. This limitation is difficult to overcome since, contrary to continuous annual crops, such as corn, spatial yield data for perennial crops (like vineyards) is much more complex to acquire due to the lack of mechanical harvesters with yield sensors that are essential for building and validating models. In the specific case of the present study area, as in many others, mechanical harvest is not even an option for the majority due to terrain limitations concerning the production model.

Climatic data from the automatic weather stations available did not have the ideal granularity (regarding quantity, location, and available variables), considering the size and heterogeneity of the study area. Further research should evaluate more robust models in defining the weather stations' areas of influence. Also, integrating satellite and model-based products like the NASA Power project (https://power.larc.nasa.gov/) with long-term climatologically averaged estimates of meteorological quantities can be helpful and constitutes a future research line for generating weather data sets where ground weather station data is missing or unavailable.

Regarding remote sensing data, the temporal NDVI profiles collected from Copernicus Sentinel-2A and 2B only allowed the model to train after 2016, despite having production data for a much broader time interval. For the current methodological approach, this is considered a limitation.

The Sentinel-2 images provide information on 13 spectral bands from 443 to 2190 nm, including the red-edge band, the short-wave infrared band, and the near-infrared narrow band. These bands benefited the prediction of vegetation variables and have been used in yield estimation in continuous annual crops. Even though vineyard is a discontinuous and perennial crop that lasts decades, with a particular management system (more so in the study area of the present study) very different from corn, wheat, or other similar crops (with 47 development stages and a myriad of interventions with potential impact on the outcome); where the goal, contrary to most annual crops, is not to maximize production (due to the quality aspects of the final product - wine); and, being perennial, it can, for example, carry-over effects from previous seasons, future research should evaluate the integration of alternative and/or more specific multispectral based VI data, such as LAI, or even explore the use of SAR and LIDAR data as potential future developments in this field for estimating in a wide scale range.

Finally, being a prediction model, this DL approach falls short of interpretability and, unlike more common inferential models, is a black-box model for making predictions.

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