Scuola Universitaria Superiore IUSS Pavia

***In Climate Veritas*: Methodologies for investigating the impact of climate variability on wine grape productivity in Italy**

A Thesis Submitted in Partial Fulfilment of the Requirements
for the Degree of Doctor of Philosophy in

HYDROMETEOROLOGICAL, GEOLOGICAL, CHEMICAL AND ENVIRONMENTAL RISK (HYRIS CURRICULUM)

Obtained in the framework of the Doctoral Programme in

Understanding and Managing Extremes

by

Laura Teresa Massano

2024

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ABSTRACT

Viticulture is a crucial sector in Italy's economy, largely dependent on weather and climate. Grapevines, as perennial plants, may be productive for maximum fifty years, a time scale for which climate variability can be relevant. In this respect, global climate warming represents an additional challenge for this cultivation, and Italy, being a climatic hotspot, is expected to experience particularly severe effects associated with climate change.

This work presents and tests two methodologies for investigating the impact of climate variability on wine grape productivity. The first methodology uses bioclimatic indices calculated on fixed calendar dates and is applied at both regional and local scales. The second methodology employs phenological and water balance models to compute ecoclimatic indices based on phenological stages of wine grape at the local scale.

For the first method, bioclimatic indices are computed using temperature and precipitation observations from the E-OBS dataset, the atmospheric reanalysis SPHERA, and the climate simulations from the CNRM-ALADIN regional climate model and the CNRM-AROME high-resolution convection-permitting model. These indices are then correlated with wine grape productivity data. The regional-scale analysis is based on productivity data provided by the Italian National Institute of Statistics from 1980 to 2019 (a 40-year period). The productivity data at the local scale are provided by two private Italian wine consortia, namely the Consorzio Tutela del Franciacorta in the north of Italy and the Consorzio Vino Nobile di Montepulciano in central Italy, over the time periods 1997-2019 (23 years) and 1989-2019 (31 years) respectively.

After conducting a single correlation analysis between bioclimatic indices and productivity, a multi-regressive model is constructed. The comparison between single and multiple regression approach shows that, in most cases for the area and period under consideration, a linear combination of bioclimatic indices increases the fraction of productivity variability explained by the statistical model. The analysis at local scale, performed using SPHERA, CNRM-ALADIN and CNRM-AROME, improves the results at regional scale, showing statistical significance in regions where the model was not able to explain the yield variability, despite using a shorter time series.

The second methodology ensures a more accurate representation of the plants' development, being based on ecoclimatic indices derived by phenological and water balance models driven by climate observations from E-OBS. A sensitivity analysis is performed on the phenological model to adapt it to the case study. The study correlates ecoclimatic indices with wine grape productivity provided by Italian wine consortia at a local scale. The significant correlation obtained in most cases confirms the positive or negative influence of ecoclimatic indices on productivity as expected based on previous studies. A multi-regressive model is then constructed to identify the indices that have the greatest impact on productivity variability. The selected ecoclimatic indices are proven to be good candidates for yield modelling. This methodology can be applied to future climate projections and used to investigate environmental changes and their potential impact on grape yield in the future.

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“This is for the possibility that guides us
and for the possibilities still waiting to sing”

Andrea Gibson

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1. INTRODUCTION

1.1 STATE OF THE ART AND MOTIVATION

Climate plays a central role in viticulture, influencing grape productivity and wine typicity (Jones, 2018; Spielmann & Charters, 2013). The development of the vine is influenced by various environmental factors including temperature, rainfall, and solar radiation. The expected changes in climate variability may pose a challenge to the wine industry since the productivity of a vineyard may last up to fifty years. The climate, and therefore climate change, affects grape production, but also the composition and quality of wine, potentially altering the geography of high-quality wine production (Van Leeuwen et al., 2024). Understanding the relationship between climate and viticulture is thus essential to assess the potential impact of climate change on grape productivity and to provide winegrowers with the knowledge to implement efficient adaptation strategies (Battaglini et al., 2009). The main driver of phenology is temperature, which affects the growing cycle (White et al., 2006). Excessively high temperatures can adversely affect productivity and quality (Drappier et al., 2019; Jackson & Lombard, 1993). Higher temperatures advance phenology and could shift flowering to a cooler, less favourable season, reducing yields (Sadras & Moran, 2013). The combination of rising temperatures and reduced rainfall will lead to a serious risk of drought. Water deficits have a negative impact on production. In fact, under drought conditions, the plant produces fewer bunches per shoot (Guilpart et al., 2014).

In 2022, Italy was the world's leading wine producer, with almost 50 million hl produced (49.8 million hl, according to International Organisation of Vine and Wine (OIV) statistics 2022), and the second-largest wine exporter, with a value of 7.8 billion euros and 21.9 million hl exported (OIV, 2023). Italy is also a climate change hotspot, i.e. a region where the impacts of climate change on the environment and human activities are expected to be particularly severe, and, despite the availability of adaptation strategies, rapid changes in climate conditions pose a significant risk to the wine sector (Mozell & Thachn, 2014).

Many studies have investigated the relationship between climate and wine grape, using climate observations, climate simulations and crop models (Ferrise et al., 2016; Fraga, 2019; Jones et al., 2012; Moriondo et al., 2011). These studies can be divided in two main categories. The first one includes studies using crop-specific bioclimatic indices, i.e. based on climatic variables for a particular season or time interval and investigates how those indicators have changed in the past and/or are expected to change in the future (Adão et al., 2023; Badr et al., 2018; Gaitán & Pino-Otín, 2023; Gopar-Merino et al., 2015; Piña-Rey et al., 2020). The second category focuses on the phenological development of the plant, considering how the time of occurrence of a particular phenological phase changes over time. This kind of study uses crop models (i.e. phenological and water balance models) to compute indices tailored to the phenological development of the specific plant (hereafter: ecoclimatic indices) (N. Brisson et al., 2003; Buis et al., 2015; Doutreloup et al., 2022; Moriondo et al., 2011; Zito et al., 2023).

Both categories mostly focus on the suitability of a region to harvest wine grape or on the potential shift in the quality of the wine produced (Dal Monte et al., 2019; Jones et al., 2005; Van Leeuwen & Darriet, 2016), both being key assets for the wine industry, especially in fine-wine regions. On the other hand, research on the impact of climate variability on wine grape productivity is still very limited. This work aims to reduce this gap by analysing the relationship between climate variability and wine grape productivity in Italy, both at the regional and local scale, using the two above-described methodologies.

1.2 OBJECTIVES

The aim of this thesis is to offer fresh insights into the relationship between recorded wine grape productivity and the climate variability either observed or simulated with climate models over Italy. The purpose is to propose and evaluate a new methodological framework for the study of climate impact on wine grape productivity. This research develops two methodologies based on bioclimatic and ecoclimatic indices, calculated using climatic observations, reanalysis products, and model simulations, to explain the variability in wine grape productivity at both regional and local scale, NUTS 2 (Nomenclature of Territorial Units for Statistics) and NUTS 3, respectively.

The proposed methodological framework can be applied to wine growing regions in different geographical areas and periods, also opening the opportunity to investigate changes in wine productivity even under future climate scenarios. Furthermore, this work could provide knowledge to support winegrowers in enhancing their level of adaptability and sustainability, as they express the need for more information in this respect (Battaglini et al., 2009). It also may serve as a foundation for implementing new climatic services or parametric insurance models.

To achieve this aim, several steps are designed and implemented as follow:

The first chapter presents a new application of bioclimatic indices to directly explain the variability in wine grape productivity at the NUTS 2 scale in Italy. Bioclimatic indices, recommended by the International Organisation of Vine and Wine (OIV, 2012), are computed using observed temperature and precipitation from the E-OBS dataset at a spatial resolution of 0.1° in latitude and longitude (~11.1 km; Photiadou et al., 2017). The computed indices are then correlated with grape productivity data provided by Italian National Institute of Statistics (ISTAT) from 1980 to 2019. Single and multi-regressive approaches are used to investigate both long-term and interannual variability. The multiple regression approach is used to account for the interplay of the bioclimatic indices in explaining the total productivity variability.

In the second chapter, the previously developed methodology is applied at the local scale, using climate models in addition to observations. The climate model used are a regional climate model (RCM), and a convection-permitting model (CPM). CPMs are km-scale climate models that can explicitly resolve convection (Fosser et al., 2020; Kendon et al., 2021) and their use in impact studies is increasing due to their better representation of extreme precipitation events or fine-scale phenomena (Chapman et al., 2020, 2023; Slater et al., 2022). In particular, the potential benefits of using a CPM, instead of a RCM, to represent productivity variability at the local scale is assessed in this chapter. Bioclimatic indices are calculated using climate data from CNRM-AROME (CPM) (Caillaud et al., 2021), CNRM-ALADIN (RCM) (Nabat et al., 2020), SPHERA reanalysis (Cerenzia et al., 2022), and the E-OBS dataset. CPM and RCM simulations are provided by Centre National de Recherches Météorologiques (CNRM), while SPHERA reanalysis is a product of ARPAE-SIMC (the hydro-meteo-climate service of Emilia Romagna region, Italy). The CPM simulation is validated against the SPHERA reanalysis, which serves as reference for this study, and compared to the RCM simulation. The validation of CPM is also performed against E-OBS dataset because, despite some previously documented limitations (Hofstra et al., 2009; Kyselý & Plavcová, 2010), it is commonly used for model validation. Consorzio Tutela del Franciacorta (FRA) and Consorzio del Vino Nobile di Montepulciano (MON) have provided data on wine grape productivity, which are then correlated with the bioclimatic indices over the period 2000-2018. Both single and multiple regressions are used to investigate whether a linear combination of bioclimatic indices increases the proportion of total productivity variability explained. This chapter highlights the significance of addressing the problem at various scales and introduces climate models as a tool to investigate it. This supports the generalizability of the presented methodology.

Bioclimatic indices are a valuable tool for examining the impact of climate variability on grape productivity. However, they have limitations as they are based on fixed calendar dates that may change with a changing climate. To address this limitation, Chapter 3 presents a different approach based on ecoclimatic indices and discusses their ability in explaining the variability of wine grape productivity at local scale. The ecoclimatic indices differ from the previously used bioclimatic indices as they are calculated based on specific phenological phases rather than fixed calendar dates (Caubel et al., 2015; Zito et al., 2023). Validated phonological and water balance models are used to identify critical periods, which can be adjusted to variety and canopy geometry information. The indices are computed using E-OBS climate variables into the phenological and water balance model and are then correlated with grape productivity data provided by FRA and MON consortia. A multi-regression model is used to identify the linear combination of indices that maximises the explained productivity variability.

The methodology applied in the previous chapters made use of both bioclimatic and ecoclimatic indices that can serve as a basis for climatic services for the wine sector, such as the one implemented by the European project MED-GOLD. Therefore, the fourth and last chapter presents the evaluation of an already implemented climatic service to show a possible application of the indices such as the ones discussed above. The work presented is based on a training given by MED-GOLD experts, during which the author had access to the dashboard developed within the project on the Portuguese and Hiberian peninsulas.

The final chapter presents a case study on the MED-GOLD climate service for the wine industry (Dell'Aquila, 2020; Dell'Aquila et al., 2023) applied in the Douro region of Portugal. The availability of data and the interest expressed by the experts involved in the project determined the choice of regions. The study evaluates the performance of the seasonal forecast for specific indicators used to prevent fungus disease and sunburn in grapes (Chou et al., 2023). This type of climate service for viticulturists is crucial to prevent losses. Previous studies on the climate service market, such as Vaughan et al., (2019, 2017) and Cortekar et al., (2020), have not addressed the issue of access fees to climate services. This chapter presents various scenarios that link the reliability of seasonal forecasts to the decision-making process of the user. The scenarios are based on the hypothetical behaviour of farmers: one relies solely on the climate service, another does not consider the service, and a third combines the information from the service with their own experience. Based on these scenarios the study proposes an annual service fee, which is linked on the accuracy of seasonal forecasts and the potential savings and losses of grape growers with micro holdings (≤ 1 ha). Although the bioclimatic index and region of interest used in this chapter differ from those previously discussed, this section demonstrates a practical application of the scientific principles mentioned earlier. It also offers an economic assessment of a climatic service, which enhances the completeness of the work.

The studies presented in chapter one and four have been published as a peer-reviewed papers (Massano et al., 2023; and Nam et al., 2024), one manuscript extracted from chapter two (Massano, Fosser, et al., 2024) has been submitted for the publication and one extracted from chapter three (Massano, Bois, et al., 2024) will be shortly submitted to international scientific journals.

2.ASSESSMENT OF CLIMATE IMPACT ON GRAPE PRODUCTIVITY: A NEW APPLICATION FOR BIOCLIMATIC INDICES IN ITALY

Abstract

Italy is a world leader for viticulture and wine business with an export valued 7 billion of euros in 2021, and wine being the second most exported product within the national agri-food sector. However, these figures might be threatened by climate change and winegrowers call for more reliable local information on future impacts of climate change on viticulture.

The study aims to understand the impact of climate on wine production in Italy using grape productivity data and bioclimatic indices. Using temperature and precipitation observations from the E-OBS gridded dataset, a set of bioclimatic indices recommended by the International Organisation of Vine and Wine guidelines is calculated and correlated with grape productivity data at the regional scale (Nomenclature of territorial units for statistics, NUTS, level 2) over the last 39 years (1980-2019). The study investigates how both long-term change and natural variability of the bioclimatic indices impacted on grape productivity. Both single and multi-regression approaches are applied to assess the portion of grape productivity variability explained by the selected indices.When the single-regression approach is applied, the correlations between bioclimatic indices and grape productivity explain up to the 45% of total production variability, however they are statistically significant only in few regions. Conversely, the multi-regression approach improves the proportion of variance explained and gives statistically significative results in region where the single regression is not statically significant. The multi-regressive approach shows the added value of considering the interplay of different bioclimatic indices in explaining the overall variability of productivity. The possibility of using bioclimatic indicators as a proxy for grape productivity provides a simple tool that grape growers, wine consortia and policy makers can use to adapt to future climate.

2.1 INTRODUCTION

Viticulture is tightly dependent on weather and climate. Over the centuries, winegrowers have adapted to climatic conditions and found the best practices to successfully grow vines in different geographical areas. However, this equilibrium between climate and viticulture could be challenged by climate change (Palliotti et al., 2018). As highlighted by Monteleone et al., 2022, climate change has been considered in different studies in the assessment of crop vulnerability. The impact of climate variability and change on grapes has been the subject of many studies, showing how rising temperatures and changing rainfall patterns can affect grape growth (Droulia & Charalampopoulos, 2021; Jones, 2003, 2007; Lena et al., 2012; Schultz, 2016). Temperature is the main driver for phenology (De Cortázar-Atauri et al., 2017) and a warmer climate may lead to an anticipation of the phenological phases and to a shortening of the growing cycle, which influence the quality of the harvest (Bock et al., 2013; G. C. Koufos et al., 2022). A change in the life cycle timing also increases frost risk, as budburst occurs earlier, when frost events are still likely to occur (Mosedale et al., 2015; Sgubin et al., 2018) while variations in the precipitation pattern can increase the exposure to pest and diseases (Bois et al., 2017). Furthermore, important shifts in viticulture suitability are expected in many traditional wine-producing regions, including Italy, that can lead to a decline in production (Hannah et al., 2013; Moriondo et al., 2013; Sgubin et al., 2023).

In Italy, wine represents the second most important exported product within the national agri-food sector, valued 7 billion euros in 2021, growing by 12.4% compared to 2020 and 51.5% compared to 2012 (Del Bravo et al., 2022). With almost 10% of the world area devoted to wine production, Italy has been in 2022 the first wine producer in the world (49.8 million hectolitres), followed by France (45.6 Mio hl) and Spain (35.7 Mio hl) (OIV, 2023).
Italian viticulture is a complex mosaic of appellation laws, driven by different climatic and environmental conditions and characterised by different vineyard management and resource optimisation strategies(Miglietta & Morrone, 2018). From a climatic point of view, Italy is classified as hot summer Mediterranean climate (Koppen-Geiger classification by Beck et al., 2018), with dry summers and wet winters, but the southwest is characterised by dryer conditions, especially inland, while the northeast is wetter and the complex orography can be characterised by very cold conditions (Fratianni & Acquaotta, 2017). Consequently, each region implements different cultivation styles, selected according to the needs of the area and the local climate. Thanks to this heterogeneity, Italy exhibits a high cultivar diversity hosting the top 80 most cultivated grape varieties (OIV, 2017). For premium wines in particular, the link between the type of wine produced and the home territory is of paramount importance, in terms of the grape variety selected, the soil property and viticultural practices used. This link is reflected in detailed specifications for vintage management and winemaking techniques (Gori & Alampi Sottini, 2014; Meloni et al., 2019).

Being part of the Mediterranean region, Italy is a climate hotspot, i.e., a region where the impact of ongoing and future climate change on the environment and human activities are expected to be particularly severe (Giorgi, 2006; Lionello & Scarascia, 2018; Tuel & Eltahir, 2020). In the past 20 years, European winegrowers already experienced the effect of higher temperatures and more frequent drought conditions on their activity. Those effects include variation in harvestable quantities, increase of pests and diseases, changes in phenology, increase in frost risk (Di Carlo et al., 2019; Van Leeuwen et al., 2019). In Italy the main effects reported are a decrease in quantity, an increase in diseases but also a higher wine quality (Battaglini et al., 2009). However, other factors, besides climate variability and change, can impact on wine production and productivity. The market can influence the choice of cultivars towards more profitable varieties, while viticultural practice can play a major role in ensuring a steady yield through the years (Basso, 2019; Vinatier & Arnaiz, 2018). The most common adaptation strategies implemented to cope with the adverse effects of climate, are changes in rootstock, in pruning techniques and/or soil management that together with irrigation are useful against sunburn and heatwaves (Fraga, 2019; Keller, 2010a, 2010b). Also, the selection of new varieties can improve the drought resistance (Hayman & Longbottom, 2012), however the application of such a strategy in Italy would require a modification of the denomination law. Despite the possible adaptation strategies, a rapid change in climate conditions could place a strong risk on the sector especially in Italy, and winegrowers are calling for more reliable local information on future impacts of climate change on viticulture (Battaglini et al., 2009; Moriondo et al., 2011; Mozell & Thachn, 2014). Several approaches have been proposed to answer their call (Ferrise et al., 2016; Sgubin et al., 2023). The most common is based on bioclimatic indices developed from climate variables for specific plants and crops to effectively describe the plant-climate interactions (Santillán et al., 2020; J. A. Santos et al., 2020; Teslić et al., 2018). The International Organisation of Vine and Wine (OIV) suggests a range of bioclimatic indices tailored to viticulture, based on temperature and heat accumulation (OIV, 2012, 2015). In addition, Badr et al. (2018), considering the work of (Blanco-Ward et al., 2007), suggest the use of precipitation-based. Bioclimatic indices are often used to assess a region's suitability for viticulture or for zoning purposes. (Cardell et al., 2019; Irimia et al., 2013; G. C. Koufos et al., 2018; Mavromatis et al., 2022; J. A. Santos et al., 2012), but also used in relation with phenology and alcohol concentration (Dalla Marta et al., 2010; Teslić et al., 2018). To assess the impact on climate change and variability, bioclimatic indices are often analysed in correlation with specific phenological phases or harvest dates (G. Koufos et al., 2014). However, these types of datasets do not give indication on productivity. Alternatively phenological or crop models (e.g. Andreoli et al., 2019; Bonfante et al., 2017; Brisson et al., 2003) can be used to determine the wine production from climate variables, but their calibration requires a huge amount of input data (atmospheric variables minimum and maximum temperatures, radiation and rain-fall, soil hydrology and composition, variety characteristics, vineyard management information etc.) and thus the scalability of their results is limited. Fraga et al., (2012) and (J. A. Santos et al.,

2011) proposed a different approach developing complex statistical tools to estimates yield under present and future climate conditions for a small area in the Douro region.

This study aims to bring new insight on the link between climate and grape production developing a simple statistical model that could support winegrowers in adapting to climate change. The present work focuses on Italy, at NUTS2 (Nomenclature of territorial units for statistics, level 2) scale, and specifically links grape productivity data (q/ha) for wine production with wine-relevant bioclimatic indices. To the best of the author's knowledge of the existing literature, this is a new application of bioclimatic indices and offers a viable alternative to the use of phenological information or harvest dates to assess the impact of climate variability and change on viticulture. Single and multi-regressive approaches are used to determine to which extent bioclimatic indices can explain the changes in Italian grape productivity over time at regional scale. The investigation is conducted on the raw data and on the high frequency component of the time series (i.e., interannual), to assess the impact of both climatic trends and interannual climate variability. The proposed methodology can be easily applied in other countries and used to predict changes in wine productivity under future climate scenarios. In addition, it can represent the base for developing new climatic services and parametric insurance models (Cesarini et al., 2021).

2.2 Data and Methods

2.2.1 Grape productivity data

The Italian National Institute of Statistics (ISTAT) collects yield data for several agricultural activities in freely available yearly publications; For the wine industry, ISTAT provides the amount of grape harvested for wine production (in quintals) and the extension of the vineyards (in hectares) from 1980 onwards. For the period investigated here, i.e., 1980-2019, the data are not homogenous over time in terms of spatial aggregation. Between 1980 and 1993, and from 2006 to 2019, grape yield data are provided at provincial level (NUTS3), from 1994 to 2000 at regional level (NUTS2), and from 2000 to 2005, at national level only (NUTS0). Thus, data have been homogenised on a spatial aggregation maximizing the temporal coverage. The national scale is discarded since it cannot properly account for the geographical variability of viticulture in Italy. Moreover, with only one harvest a year, the NUTS3 time series is too short (13 years) for the purposes of this study. Therefore, the NUTS2 resolution is chosen for the following two reasons: first, it is the best compromise between temporal coverage and spatial aggregation given the dataset characteristics (i.e., it allows the longest possible time series), and secondly because viticultural policies are regulated at regional level. Thus, when NUTS2 data are not available, the quintals of grape harvested, and the hectares devoted to vineyards provided at NUTS3 level are aggregated to NUTS2 level by computing the yearly sum of the provinces within the same region for the periods 1980-1993 and 2006-2019. This operation produces a NUTS2-aggregation time series covering the periods 1980-2000 and 2006-2019 (35 years), which can frame the spatial variability of grape productivity with enough detail, partially considering local policies and viticultural practice. Grape productivity, here defined as grape yield (q) over hectares of vineyards, is used to investigate the impact of climate on wine production. Employing productivity instead of grape production allows the analysis to be independent from the changes in vineyard area.

2.2.2 Bioclimatic indices

An overview of the bioclimatic indices used in this study, with their formulas and acronyms, is presented in Table 2.2.1 . Following the OIV recommendations, five indices based on temperature are selected:

1. Mean temperature during vegetation period (TmVeg): daily mean temperature between 1st April to 31st October (Jones et al., 2005). The growing-season temperature plays a key role in determining the timing of the phenological phases with higher TmVeg leading to an anticipation of the phenological cycle (Malheiro et al., 2013). TmVeg temperatures above 24°C and below 13°C are classified as unfavourable for vine cultivation (Eccel et al., 2016).

2. Heliothermic Huglin index (HI): calculated as daily average between mean and maximum temperatures, relative to the baseline temperature of 10 °C, when positive, otherwise equal to zero. Then the sum over the period 1st April - 30th September is corrected by a coefficient of day duration. The 10 °C temperature commonly defines the physiologically active state of the vine, i.e., the baseline temperature at which the vine begins its growth cycle (Huglin M, 1978). Higher HI allows increased sugar content in the grapes, which can be desirable depending on the wine type. A climate with HI above 3000 degrees day is classified as "very warm" and is associated to plant stress (Tonietto & Carbonneau, 2004) that, in turn, can lead to a reduction in production. Similarly, HI below 1200 degrees day is considered "too cold" for vine growth (Tonietto & Carbonneau, 2004).

3. Winkler degree days (WI): sum of daily mean temperatures above 10 °C from 1st April to 31st October. WI provides information about the heat accumulation during the growing season (Amerine & Winkler, 1944; Piña-Rey et al., 2020). Analogous to HI, its values are connected to the rate of vine growth and the development of the fruits. In this case the "too hot" ("too cold") threshold is suggested above 2700 (below 850) degree day (Eccel et al., 2016).

4. Biologically Effective Degree Days (BEDD): sum of daily mean temperatures between 10 °C and 19 °C from 1st April to 31st of October. Like WI and HI, BEDD uses a baseline temperature of 10 °C for plant growth, but adds a cut-off at 19 °C, above which additional

growth is unlikely to happen (Gladstones, 1992). Values of BEDD higher than 2000 and below 1000 degree day can negatively influence productivity. Gladstones (1992, 2011) proposed to adjust this index based on a daylength/latitude related factor as well as a daily temperature range factor to account for photosynthetic activity duration of grapevine. A simple version of the BEDDs is used here, with only the 19 °C cut-off used, since the focus here is primarily on time related change of climate (and therefore the effect of latitude is small), and the BEDDs were only slightly affected when the daily temperature range was used.

5. Cool Night Index (CNI): average minimum air temperature in September. The CNI is supposed to relate to the grape's quality (Tonietto & Carbonneau, 2004), where high night temperature in September might lead to lower anthocyanin levels in grapes (Moriondo et al., 2011). Low temperature during harvest period also affects grapes' quality, being quality of paramount importance for wine production, this index is here used in relation to productivity.

Two precipitation-based indices focused on precipitation are also identified:

1. Growing season precipitation index (GSP): rain accumulated from the 1st of April to the 30th of September. The GSP is relevant to assess the risk of grapevine exposure to water stress for not irrigated grapevine as by law in Italy (Blanco-Ward et al., 2007; Blanco-ward et al., 2017; Piña-Rey et al., 2020).

2. Spring Rain index (SprR; Raül Marcos-Matamoros et al., 2020): rain accumulated between the 21st of April to the 21st of June. This measures the spring wetness: dry springs delay vegetative growth, while wet springs induce higher level of vigour in the plant and increase fungal disease risk(Dell'Aquila et al., 2023).

The computation of the bioclimatic indices is based on temperature and precipitation data extracted from the E-OBS dataset, a gridded daily observational dataset based on meteorological stations across Europe (Photiadou et al., 2017; Van Der Schrier et al., 2013). E-OBS data are provided on a regular latitude-longitude grid with spatial resolutions of 0.1° (~11.1 km). The bioclimatic indices are calculated yearly for all E-OBS grid points over Italy below 1300 m s.l.a.. Above 1300 m s.l.a., in Italy, there are no vineyards besides the 2.5 ha in the Sila National Park (Calabria) and some tiny parcels in South Tyrol, too small to be relevant for this study. Then the indices are aggregated at the NUTS2 scale by averaging across the E-OBS grid-points within each region. The time series of the bioclimatic indices in Sicilia ends in 2018 (instead of 2019), due to extensive data gaps in the E-OBS dataset, both in temperature and precipitation.

Table 2.2.1 Acronyms and formulas of the bioclimatic indices used in this study.

	Definition	Formula	Suitable class range
Temperature-based	Mean temperature during vegetation period (TmVeg)	$TmVeg = T_{mean}$ between 1st April to 31th October	13-24 °C (Eccel et al., 2016)
	Heliothermic Huglin index (HI)	$HI = K \sum_{01\ Apr}^{30\ Sep} \max[(\frac{(T_{mean} - 10) + (T_{max} - 10)}{2}); 0]$ K=1.04 length of days coefficient	1200-3000 °C (Tonietto and Carbonneau, 2004)
	Winkler degree days (WI)	$WI = \sum_{01\ Apr}^{31\ Oct} max[(\frac{T_{min} + T_{max}}{2} - 10); 0]$	850-2700 °C (Eccel et al., 2016)
	Biologically Effective Degree Days (BEDD)	$BEDD = \sum_{01\ Apr}^{31\ Oct} min\{max[(\frac{T_{min} + T_{max}}{2} - 10);\ 0]; 9\}$	1000-2000 °C (Gladstone, 2004)
	Cool Night Index (CNI)	$CNI = \frac{1}{30} \sum_{01\ Sep}^{30\ Sep} T_{min}$	12-18 °C (Tonietto and Carbonneau, 2004)
Precipitation-based	Growing season precipitation index (GSP)	$GSP = \sum_{01\ Apr}^{30\ Sep} Prec$ Prec: total precipitation	200-600 mm (Badr et al., 2018)
	Spring Rain index (SprR)	$SprR = \sum_{21\ Apr}^{21\ Jun} Prec_{min}$	---

2.3 Methods

2.3.1 Trend analysis

A trend analysis for the bioclimatic indices is performed to assess the evolution of the climatic condition in Italy in the period 1980-2019 (with the exception of Sicilia, where time series cover the period 1980-2018). The analysis is also extended to productivity, production, and vineyard area to frame the state of the business. The non-parametric Mann-Kendall test is used to verify the presence of a trend with a level of significance of 5% (Hanif et al., 2022; Mann, 1945). Additionally, the magnitude of possible trend is estimated using Sen's slope estimator (Kh Aswad et al., 2020).

2.3.2 Single and multi-regressive approach

For the single-regressive approach, the Spearman correlation coefficient between the time series of individual indices and grape productivity is computed at NUTS2 scale. The threshold for statistical significance is set to 95%. Then, a multilinear regression (y=a*Index1+b*index2+c*index3 etc) analysis is performed to explore the possibility that a combination of indices explains a higher portion of the productivity variability compared to an individual index. The best subsets regression technique is applied at regional level to identify the optimal combination of indices and relative coefficients for the statistical predictive model of grape productivity. This method aims to find the subset of predictors (in this case the bioclimatic indices) that best predicts the outcome variable (productivity) using all the possible combinations of predictors, while removing the irrelevant ones to simplify the model. The validation is based on the k-fold cross validation method that accounts for non-independent predictors (Kassambara, 2017). The data are first randomly divided into k subsets (k-fold) of approximately equal size, with k equals 5. One-fold (10% of the data) serves as validation set and the remaining folds (90% of the data) as training set. This procedure is repeated k times; for every iteration, different groups of data serve as training and testing sets, and the mean squared error is computed at each time. The model prediction error, i.e., cross validation error, is computed as the average of all the mean squared errors (James et al., 2021; Kuhn & Johnson, 2013; Wassennan, 2004). When the coefficient of determination, i.e., the adjusted R squared (AdjR^2), indicates a skilful model, the multi-regressive model is used to predict past productivity based on the selected bioclimatic indices. If the Pearson correlation between observed and predicted productivity is significant at the 95th level ($p<=0.05$), the variance explained by the multi-regressive model is compared to the maximum variance explained using one index at a time, to evaluate the added value of the multi-regression model compared to the single-regression method.

The above-described analysis is performed first on raw data. Then, to isolate the interannual variability (i.e., the high frequency component) in the time series of both productivity and bioclimatic indices, the linear trend is removed from the raw series when a statistically significant trend is detected. In the time series not showing significant trends, the climatological mean is removed. The comparison of the raw data and the high frequency component correlations allows to determine the fraction of yield variability associated with the long-term trend (and possibly with a climate change signal) and the interannual (i.e., natural) variability, respectively.

2.4 RESULTS

2.4.1 Grape Productivity in Italy

Figure 2.4-1 shows the most productive areas in terms of (a) average annual productivity and (b) contribution to total Italian wine production. Some administrative regions with quite high average annual productivity, as Abruzzo and Trentino-Alto Adige (ABR, TRA > 100 q/ha), may limitedly contribute (<5%) to the national production. Vice versa, regions like Sicilia (SIC), show a low productivity, but are major contributors to the Italian wine production (>15%). This depends on the areas devoted to the vineyards (SIC ~ 137000 ha, ABR 36700 ha, TRA 15200), and to the management techniques in place.

Veneto (VEN), Puglia (PUG), Sicilia (SIC), in violet, followed by Emilia-Romagna (E-R) in red, are the most important wine producing regions in Italy explaining together more than half of the total national production (Figure 2.4-1b). Other important wine-growing regions are Toscana (TOS), Piemonte (PIE), as well as Lombardia (LOM), well-known worldwide for the quality of their wines. PIE has the highest numbers of appellation of origin (DOC, DOCG) and geographical indications (IGP) in Italy, followed by TOS, VEN and LOM (Sarnari, 2022).

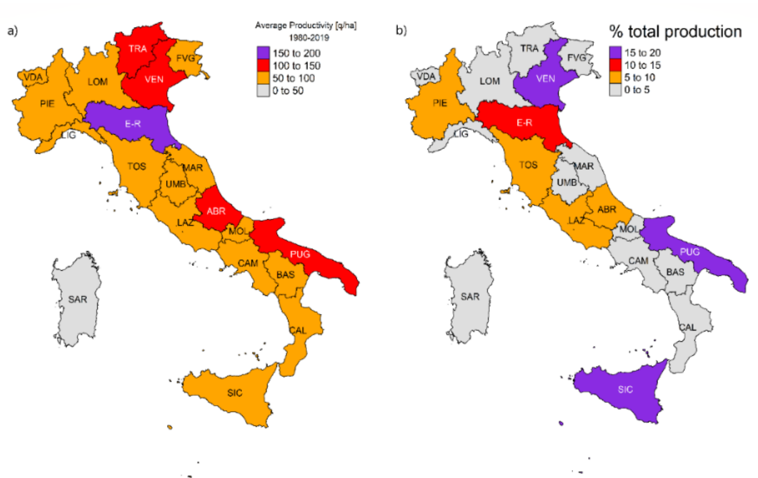


Figure 2.4-1 : Map of Italy showing a) yearly average productivity (q/ha) in the period 1980-2019 and b) contribution to the national total production in each region in percentage. The list of regions with their labels is reported in Table A 1

2.4.2 Trend analysis

Table *2.4.1* shows the trend analysis for both bioclimatic indices and productivity. The latter proves to be independent from the changes in vineyard-devoted area. Productivity shows significantly positive trends in Basilicata (BAS), Campania (CAM), Emilia Romagna (E-R), Friuli-Venezia Giulia (FVG), Puglia (PUG), Veneto (VEN), and negative only in Sicilia (SIC) and Trentino-Alto Adige (TRA), besides the strong reduction in vineyard area in all Italian regions, except TRA (Table A *1*). The temperature-based indices reflect in their trends the general temperature increase in Italy reported in literature (Bartolini et al., 2008; Gentilucci et al., 2019; Toreti & Desiato, 2008). Indices including maximum temperature, i.e., BEDD, WI and HI, exhibit strongly positive trends everywhere and significance in almost all regions. On the contrary those based on mean or minimum temperature, although positive in most cases, show small and mainly non-significant slopes, especially CNI index. This is consistent with the more limited warming in autumn and winter observed in southern Europe in the 1985-2010 period (Van Den Besselaar et al., 2015). Precipitation-based indices show a less homogenous picture, but in general characterised by positive and significant trends in the southern Italy, and negative, but mostly non-significant, trends in the central and northern regions. .

Table 2.4.1: Mann Kendal Z and Sen's Slope of the trend analysis of bioclimatic indices and productivity over the period 1980-2019. The * and bold font mark statistically significative trend (p<=0.05)

		Productivity		BEDD		HI		WI		Tm Veg		CNI		GSP		SprR	
Region	Cod.Reg.	Z	Sen's Slope [(q/ha)/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [mm/year]	Z	Sen's Slope [mm/year]
Abruzzo	ABR	0.60	0.31	4.86	**5.69***	4.77	**13.25***	4.95	**11.52***	4.95	**0.06***	1.57	0.02	2.73	**2.07***	2.06	**1.48***
Basilicata	BAS	2.45	**0.85***	5.07	**5.15***	3.81	**8.46***	4.98	**10.61***	5.16	**0.05***	3.23	**0.05***	4.47	**2.7***	1.85	1.18
Calabria	CAL	-0.79	-0.05	1.25	1.08	2.26	**2.35***	2.52	**2.4***	2.53	**0.02***	0.90	0.01	2.13	**1.68***	-0.69	-0.4
Campania	CAM	2.27	**0.35***	4.51	**4.71***	3.55	**7.44***	4.21	**9.09***	4.37	**0.05***	2.57	**0.04***	1.83	1.99	1.18	0.72
Emilia Romagna	E-R	2.73	**1.1***	4.07	**3.37***	5.21	**11.97***	4.44	**8.31***	4.60	**0.04***	0.05	0	-0.83	-0.84	0.43	0.23
Friuli Venezia Giulia	FVG	2.23	**0.63***	2.32	**2.01***	4.28	**8.7***	2.88	**3.88***	3.46	**0.03***	0.00	0	-0.98	-0.67	-0.48	-0.62

		Productivity		BEDD		HI		WI		Tm Veg		CNI		GSP		SprR	
Region	Cod.Reg.	Z	Sen's Slope [(q/ha)/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [mm/year]	Z	Sen's Slope [mm/year]
Lazio	LAZ	-0.57	-0.14	5.14	**4.99***	4.53	**9.8***	4.32	**10.52***	4.43	**0.05***	2.04	**0.04***	-0.13	-0.16	-0.17	-0.16
Liguria	LIG	0.25	0.13	2.85	**3.41***	3.93	**8.64***	2.83	**4.89***	3.33	**0.03***	-2.26	**-0.03***	-1.29	-1.85	-0.76	-1.05
Lombardia	LOM	0.93	0.24	4.74	**4.77***	5.74	**12.15***	5.39	**9.38***	5.51	**0.05***	0.62	0.01	-1.81	-2.4	-1.11	-1.03
Marche	MAR	-1.36	-0.6	2.06	**1.51***	3.02	**7.94***	3.25	**6.71***	3.30	**0.03***	-0.17	0	0.52	0.82	1.99	**1.7***
Molise	MOL	0.37	0.08	4.49	**4.58***	3.41	**8.05***	3.83	**7.68***	4.09	**0.04***	1.22	0.02	3.12	**3.04***	2.67	**1.86***
Piemonte	PIE	1.28	0.14	4.42	**4.6***	5.74	**10.96***	5.38	**7.43***	4.88	**0.04***	-0.98	-0.01	-1.62	-2.33	-1.27	-1.67
Puglia	PUG	2.22	**1.11***	6.65	**3.33***	3.65	**7.62***	5.12	**11.03***	5.20	**0.05***	3.72	**0.07***	4.05	**2.32***	2.64	1.27
Sardegna	SAR	-1.08	-0.22	6.07	**7.5***	4.84	**13.02***	6.62	**14.47***	6.81	**0.07***	2.97	**0.04***	-0.51	-0.59	-1.20	-0.7
Sicilia	SIC	-3.44	**-0.69***	5.76	**6.35***	4.67	**10.51***	5.47	**15.06***	5.43	**0.07***	3.19	**0.04***	2.95	**1.50***	-0.22	-0.07

		Productivity		BEDD		HI		WI		Tm Veg		CNI		GSP		SprR	
Region	Cod.Reg.	Z	Sen's Slope [(q/ha) /year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [mm/year]	Z	Sen's Slope [mm/year]
Toscana	TOS	4.20	**0.4***	0.29	0.53	0.55	1.31	0.92	1.78	0.90	0.01	0.23	0	-1.01	-1.27	-0.38	-0.42
Trentino Alto Adige	TRA	-2.24	**-0.55***	5.32	**5.37***	35.00	**10.88***	5.91	**6.92***	6.33	**0.05***	0.92	0.02	-1.13	-1.78	-1.39	-1.27
Umbria	UMB	1.50	0.38	1.99	**2.29***	1.97	**4.89***	2.20	**5.47***	2.57	**0.03***	0.47	0.01	-0.44	-0.31	0.20	0.09
Valle d'Aosta	VDA	-1.58	-0.25	5.39	**7.05***	6.55	**12.22***	5.89	**7.91***	5.24	**0.06***	0.00	0	-3.42	**-2.72***	-1.46	-1.26
Veneto	VEN	3.27	**1.03***	4.56	**5.04***	5.49	**13.6***	5.09	**9.4***	5.12	**0.05***	0.38	0.01	-1.92	-1.17	-0.46	-0.57

2.4.3 Climate-productivity relationship

The time series of the bioclimatic indices show values in classes not favourable to grapevine growth for temperature-based indices in 3 regions (out of 20) among those contributing less than 5% to the total Italian production (Figure 2.4-2b). Specifically, "too-cold" BEDD values are observed in Friuli Venezia Giulia (FVG), Trentino-Alto Adige (TRA) and Valle d'Aosta (VDA), while HI, WI and TmVeg in the "too-cold" class are found in TRA and VDA (Figure 2.4-2). However, this is not accompanied by a significant decrease in productivity (Figure A *1*), indicating on the one hand a high level of local adaptation to unfavourable climate conditions, and on the other hand the need to adapt the existing thresholds to the Alpine regions, like FVG, TRA and VDA. The occurrence of "very cool nights" is widespread in central and northern Italy, while warm nights affect southern regions (Puglia (PUG), Sardegna (SAR) and Sicilia (SIC)) but no statistically significant relationship with productivity can be found for CNI and precipitation-based indices (Figure A *1*).

During the four decades analysed, all temperature-based indices show positive correlations with the productivity over Italy, with the exception of a few regions; especially, Sicilia (SIC) is characterised by a strong negative correlation in all cases (Figure 2.4-2). This could suggest that the winegrowing practices have adapted over time to the increasing temperature (Boselli et al., 2016). The strongest and statistically significant correlations are found in the northeast Italy (VEN and E-R) and southern regions (PUG, BAS and CAM), among the regions contributing the most at the national wine production (cf. Figure 2.4-2 to Figure 2.4-1b). In VEN, HI index shows the highest correlation (almost 0.6), explaining up to the 35% of total productivity variability, while other temperature-indices (BEDD, WI, TmVeg) range from 27% to 30% of explained variability. E-R shows positive and significant correlation for BEDD and HI, between 0.35 and 0.39, accounting for up to the 15% of the total productivity variability. Similar ranges are found for the south of Italy in CAM, while the highest correlations (ϱ= 0.56) are registered in PUG and BAS, where respectively BEDD and TmVeg explain the 31% of the productivity variability. The CNI index shows significant correlations of almost 0.4 only for PIE and PUG. This is not surprising since CNI is supposed to relate to grape quality rather than productivity. However, as quality is of paramount importance in the wine sector, the CNI could be indirectly linked to grape productivity since it is common practice to select grapes in the field before harvesting in order to preserve the quality of the final product. SIC stands out, being the only Italian region showing strongly negative and significant correlations for all temperature-based indices, ranging from 0.47 (CNI) to 0.68 (TmVeg), with TmVeg explaining up to 46% of the productivity variability. Temperature seems to have a strong effect on Sicilian grape productivity and the projected increase in temperature (Bucchignani et al., 2016) could threaten production. SIC is also the only region showing a significant decreasing trend in both productivity and in vineyard-devoted area (Table 2.2.1 and Table A 1).

Precipitation-based indices show weaker correlation and no clear geographical pattern with respect to temperature-based indices. Statistically significant results both for GSP and SprR are present only in the north-western Italy. Specifically in PIE, where those indices explaining up to 14% of the variability, negative correlations suggest that an excess of rain is detrimental for the harvest, likely because of the triggering of fungus disease (Gessler et al., 2011; Launay et al., 2014). On the other hand, VDA, which is small contributor to the national wine production, presents positive and high correlations for both indices (ϱ up to 0.4). Vineyards here could be less prone to fungus disease given the low temperature of the Alpine area, where VDA is located. However, the results might also be spurious since based on only four grid points given that most of the region lays above 1300 m s.l.a..

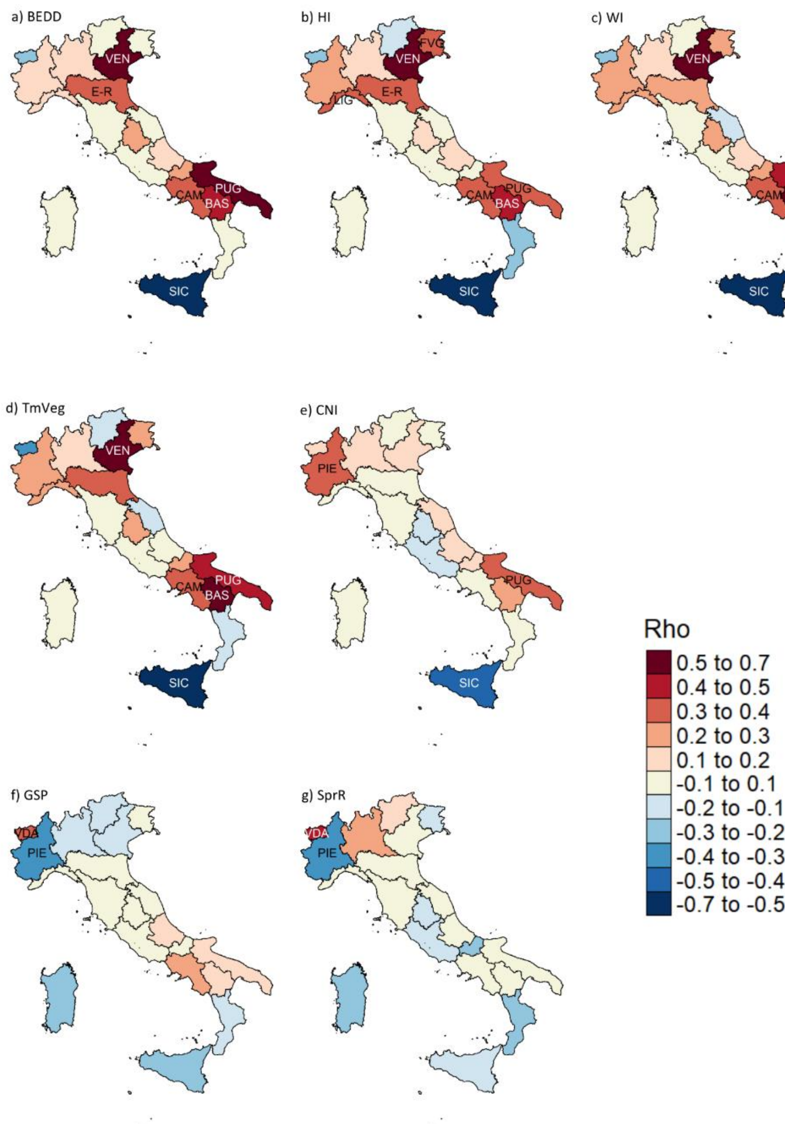


Figure 2.4-2: Maps of Italy showing the Spearman correlation coefficient between the observed productivity and the bioclimatic indices (raw data). The regions where correlations are significant are labelled.

Figure 2.4-3a shows the Pearson correlation between the observed productivity and the productivity predicted using the multi-regressive model (coefficients shown in Table A *2*), highlighting the relevant bioclimatic indices in each region. The model provides statistically significant predictions in 14 out of 20 regions and with correlations above 0.40 in 11 regions out of 20. It well represents the productivity of the biggest contributors to the Italian production, i.e., Veneto (VEN), Sicilia (SIC) and Puglia (PUG), with significant correlation between 0.45 and 0.52 and performs equally well in regions like Piemonte (PIE) and Lombardia (LOM) known worldwide for the quality of their wines. The regions where the multi-regression model has no skill (i.e., low adjR^2) are Toscana (TOS), Marche (MAR) and Abruzzo (ABR) (in grey), while is not significant in Umbria (UMB) Lazio (LAZ) and Valle d'Aosta (VDA). These regions do not show a significant correlation even with the single regression model. Several reasons could explain this result: climate may have a relatively low effect on vine growth, at least for the time being, other bioclimatic indices may be better suited for these regions; or local management practices have successfully adapted to mitigate the effects of climatic changes. Other types of intervention could also explain the lack of correlation, such as planting vineyards with more productive grape varieties, or the emergence of premium red wine, which favours grape production with a limited yield (Mannini, 2004).

The advantage of the multi-regression model is its ability to account for the interplay of temperature and precipitation-based indices on productivity, while selecting only the most appropriate ones. The multiregressive approach also indicates that precipitation-based indices can be used to correctly predict productivity, while the single-regression model rarely reveals any significant correlation with those indices (Figure 2.4-2). The most remarkable improvements are found in CAL, LOM, MOL and TRA, where the predictive model explains above 30% of the variance while none of the index alone show significant correlation with productivity (Figure 2.4-3b). Benefits are also significant for FVG (+25.3%), LIG (+8.7%) and CAM (+10.9%) and for regions important for wine production like VEN (+17.1%), PIE (+5.6%), and E-R (+18.7%). There is one cases where a worsening of the performance is found in BAS, although the extent of this decrease is less than 2%. In conclusion, the multi-regressive model substantially increases the total variability in productivity explained by bioclimatic indices in most regions compared to the single-regression approach. Almost a third of the variance in productivity is explained in both the northern and southern regions with peaks of about 50% in VEN and PUG, others non-climatic factor can contribute to the total variance (i.e., vineyard management, market laws, regulations etc).

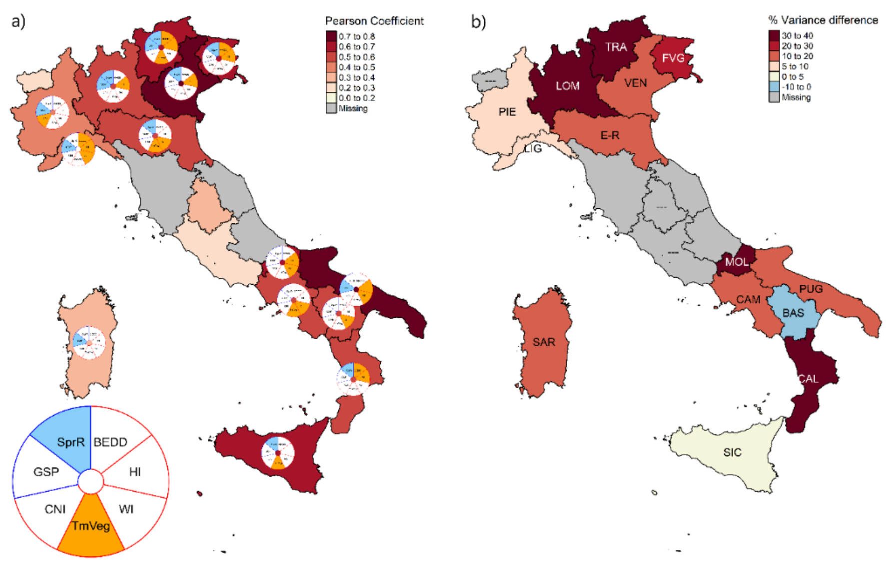


Figure 2.4-3: Maps of Italy showing raw data analysis. a) Pearson correlation coefficient betweeen the observed productivity and the productivity predicted by the multi-regression model. Grey colour represent regions were the multi-regressive model has no skill, i.e. low AdjR^2. Donuts are displayed on regions where correlations are significant (p-value <= 0.05) and indicate which indices are included in the multi-regression. Within the donuts, orange (blue) colour indicates that temperature-based (precipitation-based) indices are included in the multi-regression model for the specific region, as the example in the bottom left corner shows. b) Difference between the variance explained using the multi-regression model and the maximum variance explained by a single index. Grey colours represent regions where the multi-regression model either has no skill or correlation is not significant (indicated with "---").

2.4.4 Climate-productivity interannual relationship

This section investigates to which extent the bioclimatic indices can explain the variability in productivity at the interannual time scale, starting from a single-regressive approach (Figure 2.4-4). A similar pattern to the long-term changes is observed for both precipitation and temperature-based indices, although the correlations are substantially lower or not significant. This suggests that productivity is less affected by short-term climate fluctuations than by systematic changes with few exceptions. In LIG the temperature-based indices HI and WI show a statistically significant correlation at interannual time scale, explaining respectively the 13% and 12% of the productivity total variance. To note that HI shows a significant (positive) correlation also in the raw data, while WI does not (Figure 2.4-2 vs Figure 2.4-4). This indicates that LIG productivity is sensible to HI in terms of both its long-term trend and interannual variability, while is affected by the year-to-year variation of WI but not by his trend (Figure 2.4-2). A similar behaviour is observed in TRA for HI and WI that show significant positive correlations with productivity at the interannual time scale, explaining 21% and 18% respectively, but not in raw data. CNI in PIE also shows a positive and significant correlation with productivity, thus PIE is sensitive to CNI at both time scales (Figure 2.4-2). Regarding precipitation-based index, there are not significant result at the interannual time scale, suggesting that the year by year changing of precipitation has no impact on productivity.

The multi-regressive model outperforms single-regressive approach finding significant correlations in regions where none of the bioclimatic indices alone can explain the interannual variability in productivity (Figure 2.4-6b). Substantial improvements up to 44% are found in MOL, and up to 23% in CAL, VEN and E-R. The multi-regression allows an improvement also in LIG (+13%), and TRA (+33%).

The multi-regression analysis at interannual time scale provides significant results for 13 regions compared with the 14 obtained in the raw data analysis, and it explains similar portions of the variance (coefficient in table Table A ***3***). Finally, comparing the two multi-regression analysis (Figure 2.4-6a compared to Figure 2.4-3a), one can notice that most of the regions showing predictability (PIE, LIG, FVG, VEN, E-R, CAM, CAL, SIC, TRA) are sensible to both long-term changes in the bioclimatic indices and their year-to-year variability. Instead, regions like LOM and PUG, are affected only by long-term trend and just UMB is affected only by interannual variability.

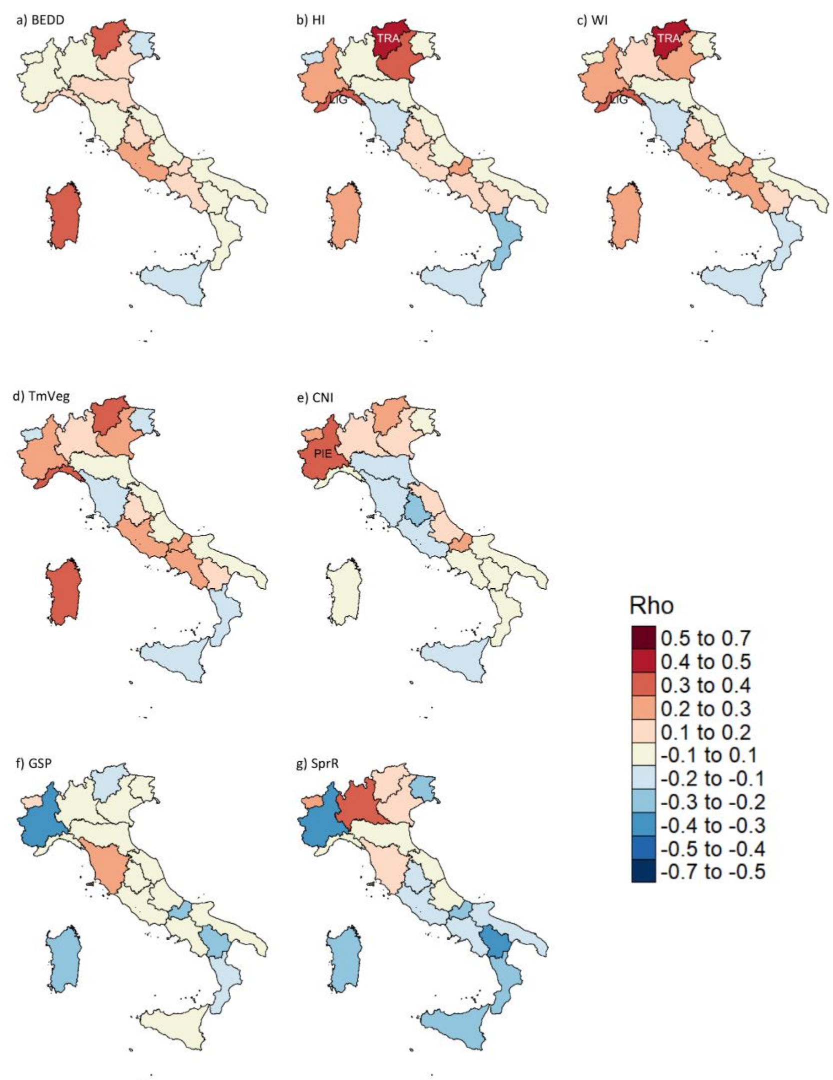


Figure 2.4-4: as Figure 2.4-5., but at interannual time scale. Maps of Italy showing the Spearman correlation coefficient between the observed productivity and the bioclimatic indices (raw data). The regions where correlations are significant are labelled.

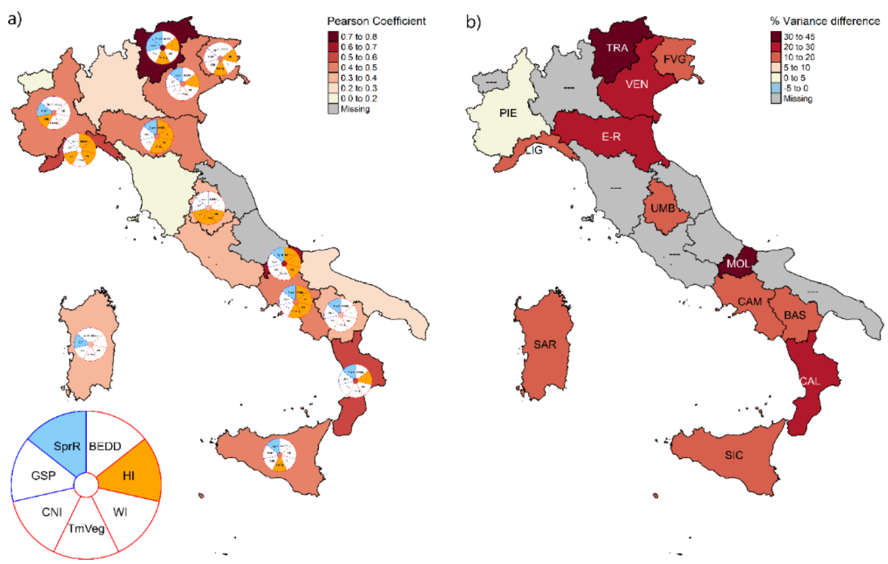


Figure 2.4-6: as Figure 2.4-3 but at interannual time scale. a) Pearson correlation coefficient between the observed productivity and the productivity predicted by the multi-regression model. Grey colours represent regions where the multi-regressive model has no skill, i.e. low AdjR^2. Donuts are displayed on regions where correlations are significant (p-value <= 0.05) and indicate which indices are included in the multi-regression. Within the donuts, orange (blue) colour indicates that temperature-based (precipitation-based) indices are included in the multi-regression model for the specific region, as the example in the bottom left corner shows. b) Difference between the variance explained using the multi-regression model and the maximum variance explained by a single index. Grey colours represent regions where the multi-regression model either has no skill or correlation is not significant (indicated with "---").

2.5 DISCUSSION

The aim of this study is to explore, for the first time, a direct statistical relationship between the bioclimatic indices commonly used in viticulture and grape productivity in Italy. The research, conducted at the regional scale (NUTS2) in Italy, use 35 years of wine grape productivity data from ISTAT and climate variables from the observational dataset E-OBS. To understand to what extent the selected bioclimatic indices can explain the changes in grape productivity in the past, both single and multi-regressive approaches are investigated. In order to compare the impact of long-term changes and inter-annual variability, the analysis is carried out on both raw data and the data after the removal of long-term tendencies (see e.g. G. C. Koufos et al., 2022).

The single-regression approach applied on raw data shows mainly positive correlations between productivity and temperature-based indices, highlighting how vineyard management has adapted over time to the increased temperature. Interestingly, for regions contributing the most to national wine production, like Veneto (VEN), Puglia (PUG) and Emilia-Romagna (E-R), a single index can explain up to 35% of the variance in productivity. Similar results are found analysing data at interannual time scale, with mostly positive correlations, although the correlations are substantially lower and rarely significant.

In Piemonte (PIE, north-western Italy), negative correlations are found for precipitation-based indices, suggesting that an excess of rain could lead to higher risk of fungus disease such as downy mildew and be detrimental for the harvest. In this region, a strong link between precipitation during spring and downy mildew treatments have been shown also in Salinari et al., 2006. Negative correlations with precipitation-base indices are also found at the interannual time scale in PIE, as well as in southern regions where rainfall is usually scarce, although these correlations are not statistically significant.

Overall, the interannual climate variability impacts less on productivity than the long-term trends. The multi-regressive model, taking advantage from the interplay of temperature and precipitation-based indices, proves to be a powerful tool to predict Italian productivity over most regions, especially for raw data, i.e., for long-term tendencies. The multi-regressive model can explain up to 54% variability in productivity at interannual time scale in Trentino Alto Adige (TRA), and up to 52% in Veneto (VEN) and Puglia (PUG) at long term variability. Furthermore, this leads to large improvements in the explained productivity variance (e.g. in Trentino Alto Adige (TRA) the increase is 39% for raw data, and 44% in Molise (MOL) at interannual time scale), even when none of the bioclimatic indices alone exhibit significant correlations with productivity. The remaining unexplained variance can depend on other factors than climate that range from viticultural practices to quality of the data collected. A complete picture of all the factors contributing to the total variability require additional investigation and falls out of the scope of this work.

The study highlights the need for better quality data, including its metadata, and the active involvement of local businesses and stakeholders in impact studies to better frame the most relevant issue that they face due to climate variability both in the short- and long- term. In fact, vineyard management, soil type, variety choice, policies and the market can all affect grape productivity, in addition to climate and weather. A limitation of this research is that this information is not included in the ISTAT database.

2.6 Conclusions

This study investigates the impact of bioclimatic indices on wine grape production in Italy and results in the development of a multi-regressive model to simulate past productivity changes at the regional level. The methodology represents a novelty with regard to the use of bioclimatic indicators, which are most often used to assess regional suitability for viticulture, but without directly relating them to productivity. The predictive models explain up to 52% of the historical harvest variability and thus show potential for being a valuable tool to estimate future changes in productivity when used in conjunction with seasonal forecast and/or future climate projections. In addition, the proposed methodology tested for Italy can be easily applied to other countries and regions as well as at local scale. The involvement of wine consortiums could improve quality, resolution and information regarding the data and enhance the knowledge on specific climatic challenges the wineries are facing.

2.7 Summary

This chapter investigates the relationship between bioclimatic indices computed using the observational dataset E-BOS and grape productivity at regional scale. Both single and multiple regression approaches are applied, and both interannual and long-term variability are considered. The multi-regressive model generally increases the portion of productivity variability explained compared to the single index. Furthermore, the impact of interannual climate variability on productivity is less significant than that of long-term trends. Climate variability is only one of several factors that can affect grape production. Other significant factors include agricultural practices, regulations, and market values. This work does not cover these factors.

The main limitation of this section lies in the heterogeneity of the productivity data considered and of the Italian wine sector. Productivity data collected by the ISTAT database had to be homogenised at NUTS2, and the resulting time series is 39 years long, with a 5-year gap that was not possible to fill. The Italian wine sector is heterogeneous, and each region has different regulations, needs and standards to fulfil that are, in part, an expression of the heterogeneity of the climate in the Italian peninsula. Therefore, the next chapter conducts a similar investigation but at a local scale, using productivity data from two Italian wine consortia and high-resolution climate models. Moreover, the set of bioclimatic indices is increased by adding three more indices based on minimum and maximum temperatures.

3.A LOCAL SCALE ITALIAN STUDY OF THE IMPACT OF CLIMATE VARIABILITY ON WINE GRAPE PRODUCTIVITY USING A CONVECTIVE MODEL

Abstract

Climate is tied to viticulture, as it determines the suitability of an area and influences the yield and quality of wine grapes. Traditional wine-growing regions are therefore threatened by the expected change in climate. Italy has a thriving agricultural sector, with wine production being a significant contributor. In 2022, Italy was the second-largest exporter of wine, with a value of 7.8 billion euros. In the coming decades, the wine industry is then likely to be impacted by the adverse effects of climate change.

This study evaluates the potential of convection-permitting climate models to represent the impact of climate variability on wine grape productivity at the local scale in Italy. Temperature and precipitation-based bioclimatic indices are computed by using climate data from observations, a climate reanalysis product, a regional climate model and a convection permitting climate model (CPM). The article explores the potential for predicting wine grape productivity at a local scale by regressing productivity data provided by two wine consortia in northern and central Italy onto bioclimatic time series. The results indicate a high correlation between indices and productivity, but only a few indices are statistically significant. In addition, bioclimatic indices are good predictors of wine grape productivity. However, the CPM simulation does not show any added value compared to the use of other climatic data, unless precipitation-based indices are considered.

This assessment shows the potential of convection permitting climate modelling in predicting the observed grape wine productivity and can be used as a basis for utilising CPMs in future impact studies, especially when convective precipitation is the primary impact driver or when high-resolution climatic data is necessary.

3.1 INTRODUCTION

Winegrowing has strong socio-economic impact and is one of the principal agricultural economic activities in Italy, that in 2022 was the world's leading wine producer (49.8 million hl), and second largest wine exporter, with a value of 7.8 billion euros, drop in production is expected in 2023, estimated at 43.9 million hectolitres (-12% / 2022) (OIV, 2023).

Climate plays a significant role in viticulture, determining the suitability of an area and influencing wine grape yield and quality. Over the coming decades, the wine sector is expected to be affected by climate change especially in Italy that is part of the Mediterranean climatic hotspot (Tuel & Eltahir, 2020), where the impact of climate change is expected to be more severe than the global average (Bernetti et al., 2012; Sacchelli et al., 2016). In this context, many studies investigated the impact of rising temperatures and changing rainfall patterns on grape growth (Bagagiolo et al., 2021; Gentilucci, 2020). Temperature is the primary driver for the phenological phases (Fraga et al., 2016), and a warmer climate may lead to an earlier onset of phenological phases and to a shorter growing cycle, increase frost-related risks, as budburst occurring earlier in spring, when frost events are still frequent (Lamichhane, 2021; Trought et al., 1999). Furthermore, traditional wine-producing regions, as Douro in Portugal, La Rioja in Spain, Bordeaux in France, and Tuscany in Italy, are expected to experience important shifts in viticulture suitability that can consequently causes a decline in production (Adão et al., 2023; Rafique et al., 2023; Sgubin et al., 2023; Tóth & Végvári, 2016).

A common tool to investigate the impact of climate variability and change on the wine sector is the use of bioclimatic indices, developed from climate variables for specific plants and crops (Badr et al., 2018; Chou et al., 2023; Gaitán & Pino-Otín, 2023). A set of bioclimatic indices, based on temperature and heat accumulation (OIV, 2015), was proposed by the International Organisation of Vine and Wine (OIV), while precipitation-based indices were developed by Badr et al., (2018) considering the research of Blanco-Ward et al., (2007). Bioclimatic indices are commonly used to assess a region's suitability for viticulture or zoning purposes, as well as in relation to phenology, harvest date and alcohol concentration (Dalla Marta et al., 2010; G. Koufos et al., 2014; Sánchez et al., 2019; Teslić et al., 2018). A novel application linking bioclimatic indices directly to wine grape productivity data in Italy was successfully proposed by Massano et al., (2023) at regional level.

In Italy the vineyards are planted in extremely different areas, from the coasts to the hills, in some case also at considerable altitude (Tarolli et al., 2023). The wine production system is complex and fragmented, including both small farms and large companies. To valorise the designation of origin, to guarantee a defined level of quality, to improve knowledge with the help of the technical office, and promote their wines, producers are organized in wine consortia (Consorzi di Tutela) according to the EU and national regulations (e.i. Regulation (EU) No 1308/2013, Disciplinari regionali) (Gori & Alampi Sottini, 2014; Ugaglia et al., 2019). To address this fragmentation, and account for the typicity of the wine business (Agnoli et al., 2023; Spielmann & Charters, 2013), yield data from the wine consortia and high-resolution climate data are of prominent importance for local-scale impact studies and thus for effective adaptation strategies.

In the context of impact studies at local scale requiring high-resolution climatic data, the use of km-scale convection permitting models (CPM) is increasing (Bamba et al., 2023; Le Roy et al., 2021; Tradowsky et al., 2023). Thanks to their high spatial resolution (less than 4 km), CPMs can represent convection explicitly without the need for parameterisation, thus reducing the model uncertainty associated to it (Fosser et al., 2024). Compared to coarser resolution regional climate models (RCMs), the CPMs showed to represent more realistically hourly rainfall intensity, the diurnal cycle of precipitation and the extremes and thus are consider more reliable in terms of climate projections (E. Brisson et al., 2016; Coppola et al., 2020; Fosser et al., 2015, 2020; Kendon et al., 2017). The advantages of CPMs, versus RCMs, has also been explored assessing the impact of climate change on agriculture and crop production (Agyeman et al., 2023; Berthou et al., 2019; Chapman et al., 2020, 2023)

This study assesses the potential of a CPM to represent the impact of climate variability on wine grape productivity at the local scale, by relating temperature and precipitation-based bioclimatic indices to wine productivity data provided by two wine consortia in northern and central Italy. The CPM performance is validated against climate observations and reanalysis product, as well as compared to the driving RCM simulation to investigate the add-value of the higher resolution. Single and multiple regression approaches are used to determine the extent to which bioclimatic indices can explain changes in wine grape productivity at local scale. The multiple regression approach can account for the potential interplay between the bioclimatic indices, potentially increasing the proportion of total productivity variability explained by the indices, as found in Massano et al. (2023).

3.2 DATA AND METHODS

3.2.1 Wine grape data

Wine grape yield data, as well as the hectares devoted to viticulture, are collected from two wine consortia in Italy: 'Consorzio per la tutela del Franciacorta' (FRA) and 'Consorzio Del Vino Nobile di Montepulciano' (MON). The first one lies in Franciacorta, a small (200 km2) winegrowing region in Lombardia (LOM), in northern Italy, mostly known for sparkling wine (Figure *3.2-1*a). The area is characterised by a humid subtropical climate according to the Koppen classification (Costantini et al., 2013). The Iseo lake, located at the northern border of this region, is the sixth largest lake in Italy and tempers in summer the typical heat of the plain while in winter protects the vineyards from the freezing air arriving from the north (Leoni et al., 2019). The consortium was born in 1990 thanks to the endeavour of local producers that felt the need to preserve the original production method of the Franciacorta wine. Today the consortium is composed by 200 winemakers and preserves three designations: Sebino IGT (Typical Geographical Indication), Franciacorta DOCG (Denomination of Controlled and Guaranteed Origin) and Curtefranca DOC (Denomination of Controlled Origin), known as

"Terre di Franciacorta" before 2011 (https://franciacorta.wine/en/). This analysis focuses on the designations of Franciacorta DOCG and Curtefranca DOC from 1997 to 2019 (23 years), while neglects Sebino IGT that is available only for a limited period.

The "Consorzio del Vino Nobile di Montepulciano" (MON) is located within the Montepulciano territory in Toscana (TOS) region in the centre of Italy (https://www.consorziovinonobile.it/) (Figure 3.2-1) The area is characterized by a Mediterranean climate with hot and dry summer, and mild and rainy winters (Costantini et al., 2013). The consortium preserves three designations, i.e. Vino Nobile di Montepulciano DOCG, Rosso di Montepulciano DOC and Vin Santo di Montepulciano DOC, but the study focuses on the first two designations that have the longest time series covering 31 years between 1989 and 2019.

a) b)

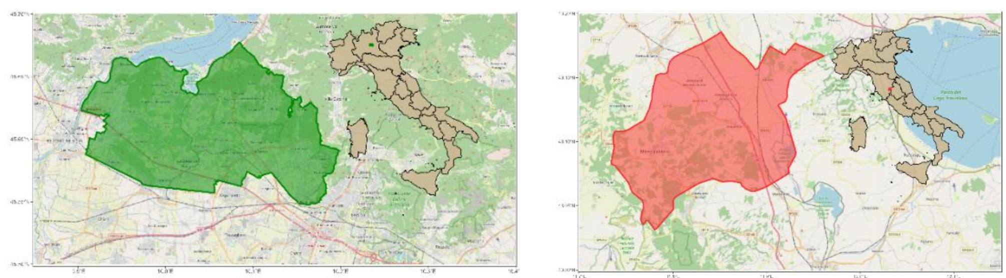


Figure 3.2-1: a) Area of Franciacorta Consortium (FRA), Lombardia (LOM), region, North of Italy. b) Area of the Consorzio del Vino Nobile di Montepulciano (MON), Toscana (TOS) region, centre of Italy.

For each wine designation, the FRA consortium directly reports the quantity of grapes harvested in quintals (q), while MON indicates the hectolitres of wine produced (hl) and the maximum percentage of the grape yield convertible into wine (70%). For the analysis, the hectolitres are converted into quintals using the maximum percentage allowed (hl/0.70), and then the productivity (q/ha) is calculated by dividing the quintals of grapes by the vineyard area.

To check the consistency of productivity data between local and regional scales, and thus contextualise this work within the broader framework of previous studies (e.g. Di Paola et al., 2023), the productivity at local scales (FRA and MON) is compared with the productivity at regional scale provided by the Italian National Institute of Statistics (ISTAT; Figure A *2*). The ISTAT provides the harvested wine grape (in quintals) and the area devoted to vines (in hectares) from 1980 onwards. However, the data are not homogenous over time in terms of spatial aggregation. Wine grape productivity data are available at the provincial level between 1980 and 1993 and from 2006 to 2019; at regional level between 1994 and 2000; at national scale while from 2000 to 2005. Following Massano et al (2023) procedure, the data were homogenised at regional level for Lombardia (LOM) and Toscana (TOS) region, where the FRA and MON consortia are respectively located, for the period 1980–2019, with a six-year gap between 2000 and 2005. Considering the overlapping periods between ISTAT and the consortia, it is found that the regional and local productivity data are significantly correlated ($p<=0.05$) for both FRA and MON (Table S3). In addition, the Welch's t-test proves that both consortium distributions are part of the regional population (Table A 4, Figure A 2 and Figure A 3).

3.2.2 Observational climate data

The observational dataset used is E-OBS, a gridded daily data set covering Europe from January 1950 to the present day. E-OBS is constructed using data from meteorological stations from the European National Meteorological and Hydrological Services (NMHSs) or other data holding institutions (Photiadou et al., 2017; Van Der Schrier et al., 2013). The analysis is based on the latest available version (v28) at 0.1 deg (~11 km). The E-OBS database is frequently used to validate climate models (Christensen et al., 2008; Jaeger & Seneviratne, 2011; Lorenz & Jacob, 2010; Retalis et al., 2016). However, some studies have pointed out limitations in the E-OBS representation of precipitation and temperature, mainly due to the inhomogeneity of the station network used for interpolation (Kyselý & Plavcová, 2010; Liakopoulou & Mavromatis, 2023; Van Der Schrier et al., 2013).

In addition to observations, the analysis uses a high-resolution convection-permitting reanalysis product, called SPHERA (High rEsolution ReAnalysis over Italy; (Cerenzia et al., 2022; Giordani et al., 2023)), produced by ARPAE-SIMC (Agency for Environmental Protection of the Emilia Romagna Region, Italy). Based on the non-hydrostatic limited-area model COSMO (Baldauf et al., 2011; Schättler et al., 2018), SPHERA dynamically downscales the global reanalysis ERA5 (Hersbach et al., 2020) assimilating regional in situ observations to improve the quality of the simulation. This new reanalysis product covers Italy at a horizontal resolution of 2.2 km with a temporal coverage of 26 years (1995-2020). SPHERA reanalysis is validated against ERA5 by Giordani et al. (2023) and show an added value for the description of moderate to severe local precipitation events, and extreme rainfall. The performance of SPHERA demonstrates that it can be a valuable resource for enhancing climate monitoring efforts by providing insights into regional climate change impacts (Giordani et al., 2023).

3.2.3 Climate model data

Two climate simulations are provided by the French Centre National de Recherches Météorologiques (CNRM) for the period 2000-2018 over Europe. The first based on an RCM model, CNRM-ALADIN, and the second based on a CPM model, CNRM-AROME (Lucas-Picher et al., 2023). The first simulation, CNRM-ALADIN (hereafter RCM) (Bán et al., 2021), has a horizontal resolution of 12.5 km and is the limited area version of ARPEGE-Climate. The second simulation, CNRM-AROME (hereafter CPM), is a convection-permitting model dynamically downscaled from CNRM-ALADIN, with a resolution of 2.5 km. Convection Permitting Models (CPMs) are non-hydrostatic models that can explicitly resolve convection for a more accurate representation of surface and orographic fields, typically they have a horizontal gridding of less than 4 km.

3.2.4 Bioclimatic indices

This study considers ten bioclimatic indices described in detail in the following and summarised in Table *3.2.1*. Eight of them, recommended by the International Organisation of Vine and Wine (OIV), are based on temperature and heat accumulation while the other two are based on rainfall accumulation.

The temperature-based indicators are:

1. Daily mean temperature during vegetation period (TmVeg), i.e. calculated between 1st April to 31st October (Jones et al., 2005). Temperature in spring plays a key role in determining the timing of the phenological events, as underlined by Malheiro et al., (2013). In general, higher TmVeg leads to an anticipation of the phenological phases, while TmVeg values above 24 °C or below 12 °C are considered unfavourable to wine-growing (Eccel et al., 2016).

2. Heliothermic Huglin index (HI), which is calculated by summing, when positive, the average between the mean and the maximum temperature, in relation to the baseline temperature, over the period from 1st April to 30th September and corrected by a coefficient of day duration. The physiological threshold for the start of the vine growth cycle is a temperature of 10°C (Huglin M, 1978; Teslić et al., 2018). The HI index is tied to vine growing and grape sugar concentration with higher HI leading to an increased vine vigour and higher sugar content in the grapes. According to Tonietto and Carbonneau (2004), a climate with a heat index (HI) of more than 3000 degrees per day is classified as 'very warm', while below 1200° is "too cold". Both these situations are associated to plant stress and thus lead to a production reduction.

3. Winkler degree days (WI), which provides a measure of heat accumulation during the growing season being the sum of daily mean temperatures above 10°C from 1st April to 31st October (Amerine & Winkler, 1944; Piña-Rey et al., 2020). Similarly to HI, WI index is linked

to the rate of growth of the vines and the development of the fruits with values between 850 and 2700 degree days being optimal for the wine production (Eccel et al., 2016).

4. Biologically Effective Degree Days (BEDD), which is the sum of daily mean temperatures, when in the range between 10 °C and 19 °C, from 1st April to 31st of October. The BEDD index uses the same baseline temperature as WI and HI indices, but considers additional vine growth unlikely to occur above the upper temperature threshold of 19°C (Anderson et al., 2012; Gladstones, 1992). As the previous temperature-based indices, too high (above 2000°) or too low (below 1000°) values of BEDD can potentially reduce productivity.

5. Cool Night Index (CNI), defined as the average minimum air temperature during the month of September. Low minimum temperatures in September increase the polyphenolics in the grapes and are beneficial for the overall quality of the harvest (Tonietto & Carbonneau, 2004). Although CIN is more related to grape quality than quantity, Massano et al (2023) found that this index can be help explaining changes in productivity especially when using the multi-regression approach.

6. Minimum temperature during vegetative period (TnVeg), which is the minimum temperature occurred during the vegetative period (1st April to 31st October). This index is important to assess the occurrence of spring frost that pose a significant risk to viticultural practices and production, the damage threshold is fixed at -2 °C but it is strictly dependent on local conditions (Sgubin et al., 2018).

7. Maximum temperature during vegetative period (TxVeg), which is the maximum temperature occurred during vegetative period. This index is useful for assessing the occurrence and the severity of summer hot-spells that can damage to vineyard thus reducing the wine productivity (Cabré & Nuñez, 2020). The heat stress threshold is set at 35°C, above which physiological damage to the vines is expected (Hunter & Bonnardot, 2011).

8. Minimum temperature during rest period (TnRest), defined as the minimum temperature during rest period, i.e. 1st November to 31st March. Useful for assessing winter severity. This index is use to determine winter severity, grapevines can tolerate temperatures as -25 °C (Düring, 1997; Lisek, 2012) , although damage can already occurs at -15 °C (Eccel et al., 2016)

The indices based on precipitation are:

1. Growing season precipitation index (GSP), defined ad rainfall accumulated from 1st April to 30th September and is used to assess the water stress for non-irrigated grapevines (Blanco-Ward et al., 2007; Piña-Rey et al., 2020), as in Italy where irrigation is only allowed in extreme cases (e.g. long drought periods).

2. Spring Rain index (SprR), which measures the amount of rain accumulated between the 21st of April and the 21st of June (Raül Marcos-Matamoros et al., 2020). This indicator of spring wetness can be related to production. In fact, while dry springs can delay vegetative growth,

wet ones can increase plant vigour but also lead to an higher risk of fungal diseases (Dell'Aquila, 2022).

Table 3.2.1: Acronyms and formulas of the bioclimatic indices used.

	Definition	Formula	Suitable class range
Temperature-based	Mean temperature during vegetation period (TmVeg)	$TmVeg = T_{mean}$ between 1st April to 31th October	13-24 °C (Eccel et al., 2016)
	Heliothermic Huglin index (HI)	$\mathrm{HI} = \mathrm{K}\sum_{01\,\mathrm{Apr}}^{30\,\mathrm{Sep}} \max[(\frac{(T_{mean} - 10) + (T_{max} - 10)}{2}); 0]$ K=1.04 length of days coefficient	1200-3000 °C (Tonietto and Carbonneau, 2004)
	Winkler degree days (WI)	$WI = \sum_{01\,Apr}^{31\,Oct} max[(\frac{T_{min} + T_{max}}{2} - 10); 0]$	850-2700 °C (Eccel et al., 2016)
	Biologically Effective Degree Days (BEDD)	$BEDD = \sum_{01\,Apr}^{31\,Oct} min\{max[(\frac{T_{min} + T_{max}}{2} - 10);\ 0]; 9\}$	1000-2000 °C (Gladstones, 1992)
	Cool Night Index (CNI)	$CNI = \frac{1}{30}\sum_{01\,Sep}^{30\,Sep} T_{min}$	12-18 °C (Tonietto and Carbonneau, 2004)
	Minimum temperature during vegetative period (TnVeg)	$TnVeg = T_{min}\ between\ 01\ Apr - 31\ Oct$	Damage threshold -2 °C (Sgubin et al., 2018)
	Maximum temperature during vegetative period (TxVeg)	$TxVeg = T_{max}\ between\ 01\ Apr - 31\ Oct$	Upper threshold 35 °C (Hunter & Bonnardot, 2011).
	Minimum temperature during rest period (TnRest)	$TnRest = T_{min}\ between\ 01\ Nov\ - 31\ Mar$	Above -25 °C (Düring, 1997; Lisek, 2012)
Precipitation-based	Growing season precipitation index (GSP)	$GSP = \sum_{01\,Apr}^{30\,Sep} Prec$ Prec: total precipitation	200-600 mm (Badr et al., 2018)
	Spring Rain index (SprR)	$\mathrm{SprR} = \sum_{21\,\mathrm{Apr}}^{21\,\mathrm{Jun}} Prec$	(Dell'Aquila, 2022)

3.2.5 Validation of climate simulation and calculation of bioclimatic indices

In this work, the observational dataset E-OBS, the climate reanalysis product SPHERA and the climate model simulations, at regional (RCM) and convection-permitting scale (CPM), are used for the calculation of the above-described bioclimatic indices. The analysis focuses on the 19 years from 2000 to 2018 that is the longest period available for RCM and CPM simulations and in common with E-OBS, SPHERA as well as productivity data from FRA and MON.

To compare the observational datasets and climate simulations among each other and on equal terms (Berg et al., 2013), they are first all remapped on a common grid, i.e. E-OBS regular grid, at ~11 km. Tests performed to investigate the effects of the remapping strategy on the climate variables showed that the results are not impacted by the chosen resolution (not shown).

Then, the climatic variables (i.e. P: Precipitation; TM: mean temperature, TX: max temperature and TN: min temperature) are computed on all available grid cells within the areas of interest (LOM and TOS). Subsequently, the consortium territory is cropped using the respective shape files of FRA and MON. Finally, the spatial average is calculated by weighing the contribution of each grid cell according to the percentage of the cell falling within the consortium. The shape file of the FRA consortium's territory is provided directly by the consortium's technical office, while the shape file for MON is created by selecting the municipality listed in the appellation regulation for the relevant denominations (i.e., Montepulciano municipality). The same methodology is used to calculate the bioclimatic indices.

The precipitation and temperature time series of the climate simulations are analysed against the observational datasets to evaluate the biases in the climatic conditions in the region of interest, prior to examine the bioclimatic indices. In particular, the CPM performance is evaluated for the common period 2000-2018 against both SPHERA and E-OBS and compared to the RCM. Although the E-OBS dataset is often used for model validation (Kyselý & Plavcová, 2010), this study has opted to use the new SPHERA reanalysis product as the reference dataset, while still including the E-OBS in the analysis. SPHERA and E-OBS time series together provide a range within which the CPM and the RCM time series are expected to fall, similar to a 'confidence interval'.

The comparison between SPHERA (E-OBS) and CPM, as well as SPHERA (E-OBS) and RCM, is carried out by computing the Spearman correlation and RSME. This allows us to analyse whether the variability of SPHERA data is reproduced by CPM and RCM simulations, and the distance between simulations and references. Additionally, the mean values of SPHERA (E-OBS) and CPM, as well as SPHERA (E-OBS) and RCM, are compared using a Welch's two-tailed t-test.

Finally, a trend analysis for both the climatic variables and the bioclimatic indices is performed to assess the evolution of the climatic condition in FRA and MON in the period 2000-2018; the same analysis is also carried out for productivity data. The non-parametric Mann-Kendall test and the Sen's slope estimator are used to determine the presence and the magnitude of trends with a significance level of 5% (Hanif et al., 2022; Mann, 1945). The assessment of possible trends aims to investigate whether the long-term component of variability may be dominant over the interannual component.

3.2.6 Single and multi-regression approach

The Spearman correlation coefficient between each bioclimatic index and wine grape productivity is calculated for both consortia area and the threshold for statistical significance is set to 95%. This analysis aims at assessing the fraction of wine grape productivity variability explained by the bioclimatic indices and the ability of climate models to represent this relationship compared to the observational datasets.

Furthermore, a multi-regressive approach is applied to determine whether a linear combination of indices can enhance the total productivity variability explained by the bioclimatic indices (Massano et al., 2023). The best subsets regression technique is used to establish the most suitable combination of indices. This approach seeks the predictor subset of bioclimatic indices that most accurately predicts the outcome variable, i.e. the productivity. It examines all feasible predictor combinations and removes irrelevant ones to streamline the model. The k-fold cross validation method is employed to identify the optimal model (Kassambara, 2017). This method performs cross-validation by randomly dividing the data into k subsets (k-fold) approximately of equal size, with k typically set to 5 or 10 (here k = 5 is used). One of the folds serves as test set and the remaining as training. This process is repeated k times, whereby varying groups of data are utilized as training or testing sets. Subsequently, the mean squared error is computed. The average of the mean squared errors of all iterations is the model prediction error (CV - cross validation error) (James et al., 2021; Kuhn & Johnson, 2013; Wassennan, 2004). The performance of the multi regressive model is assessed by the adjusted R-squared coefficient of determination ($AdjR^2$), while the p-value is used to determine statistical significance at 95^{th} level. The so optimised multi-regression model is then used to predict the past productivity, which is compared to the observed productivity using the Pearson correlation.

The performances of the single-regression and multi-regression model are assessed by comparing the maximum variance explained by each of the two statistical models. Specifically, the variance of the observed productivity is estimated in the single-regression and multi-regression models by computing, respectively, the Spearman and Pearson correlations with the bioclimatic indices.

3.3 RESULTS

3.3.1 Validation of the climate simulations

The precipitation and temperature time series of both CPM and RCM are validated against the observational datasets to evaluate the biases in the climatic conditions of the consortia (FRA and MON), which could in turn lead to biases in the bioclimatic indices. To this end, **Figure 3.3-1** for FRA, and **Figure 3.3-2** for MON, show the precipitation (P) and temperature (TM: mean temperature, TX: max temperature and TN: min temperature) time series of E-OBS, SPHERA, RCM and CPM for the common period 2000-2018. In MON, E-OBS minimum temperature time series shows a strong decrease of almost 2°C between 2015 and 2018 (**Figure 3.3-2**), which is not observed in any of the other datasets. Further investigations highlighted that this temperature fall affects the entire TOS and is inconsistent with other observational records (not shown). This E-OBS misrepresentation of the temperature field affects consequentially the mean temperature time series (**Figure 3.3-2**), the temporal correlations (Table A *5*), and is likely to be reflected in the temperature-based indices. Previous studies have shown that E-OBS underestimates monthly and seasonal average temperatures when compared to stations observations (Liakopoulou & Mavromatis, 2023). In general, both RCM and CPM show high and significant temporal correlations with SPHERA for all the climate variables in both consortia (Table A *5*), indicating that RCM and CPM reproduce the same variability of SPHERA, although the climate simulations tend to overestimate mean and maximum temperature while underestimating the minimum as reflected by the statistical differences in mean values (Table A *6*). In FRA the variability observed in E-OBS is always reproduced also in RCM and CPM simulations. The t-test confirmed that E-OBS is closer in mean value to RCM than CPM simulations.

Figure 3.3-1: Time series of mean (TM), maximum Temperature (TX), minimum (TN) temperature and precipitation (P) over FRA area for the period 2000-2018. All the time series are based on data remapped on E-OBS grid (~ 11 km).

Figure 3.3-2: Time series of mean (TM), maximum Temperature (TX), minimum (TN) temperature and precipitation (P) over MON area for the period 2000-2018. All the time series are based on data remapped on E-OBS grid (~ 11 km).

Figure 3.3-3 and **Figure 3.3-4** show the ten bioclimatic indices time series computed in the two consortia areas for E-OBS, SPHERA, RCM and CPM. All the bioclimatic indices show very high and significant temporal correlation between SPHERA and both RCM and CPM in both consortia (**Table 3.3.1**). Similar conclusion can be draw for the comparison of the climate models with E-OBS in FRA, while in MON four temperature-base indices (i.e. BEDD, WI, TnVeg, CNI) are not significantly correlated likely due to the low correlations in medium and minimum temperature (Table A 5). The correlations, especially with SPHERA, tend to be slightly higher for the CPM than for the RCM for most indices, despite the higher RMSE in the CPM (**Table 3.3.1**). The results of the Welch's t-test investigate whether the differences in the mean of the different bioclimatic indices between climate simulations and observations datasets are significant (Table A 7).

The strong correlation between SPHERA and climate simulations (**Table 3.3.1**) indicates that RCM and CPM reproduce the same variability of SPHERA, despite the statistical differences in mean values (Table A 7) . The same conclusion is valid for the comparison of RCM and CPM to E-OBS. This analysis suggests both CPM and RCM could be a valid alternative to observational dataset to investigate the impact of climate on viticulture, despite the biases affecting the climate simulations.

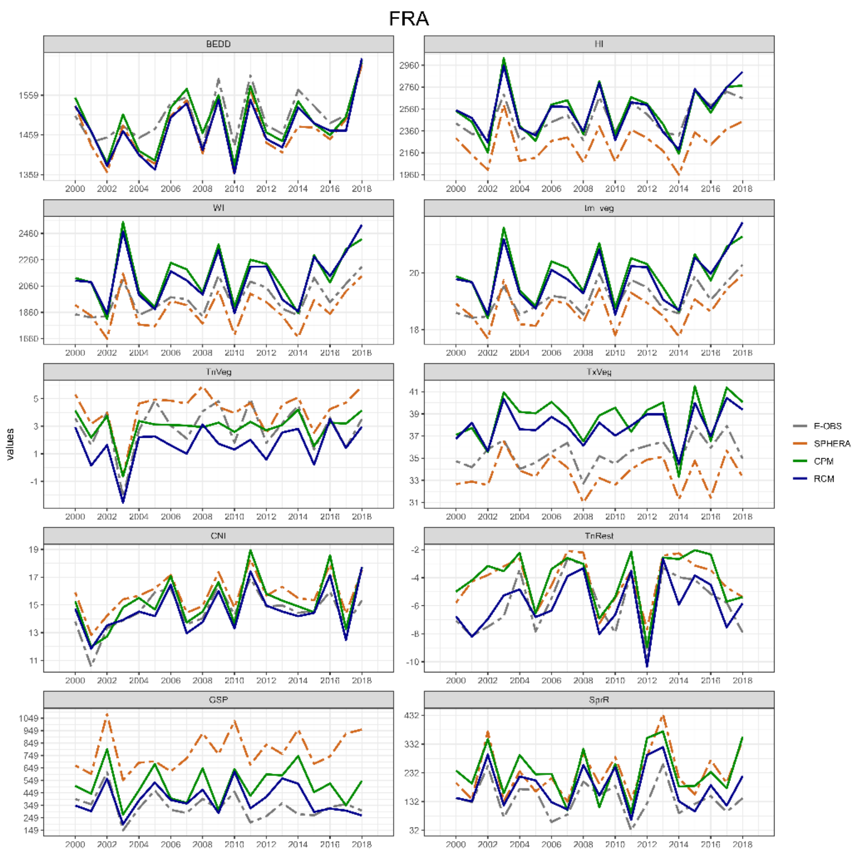


Figure 3.3-3: Bioclimatic indices time series 2000-2018, averaged on the FRA consortium area.

Figure 3.3-4: Bioclimatic indices time series 2000-2018, averaged on the MON consortium area.

Table 3.3.1: Spearman correlation coefficient and root mean square error (RMSE) of the indices time series. Bold font and asterisk (*) indicate a statistically significant result (p>=0.05)

FRA									
	SPHERA vs CPM		SPHERA vs RCM		E-OBS vs CPM		E-OBS vs RCM		
Index	ρ	RMSE	ρ	RMSE	ρ	RMSE	ρ	RMSE	Index
BEDD (GDD)	**0.97***	26.62	**0.96***	19.39	**0.85***	37.29	**0.91***	45.78	BEDD (GDD)
HI (GDD)	**0.98***	305.88	**0.96***	308.59	**0.88***	128.56	**0.87***	117.36	HI (GDD)

WI (GDD)	**0.99***	264.91	**0.98***	247.63	**0.85***	209.55	**0.85***	191.23	WI (GDD)
TmVeg (°C)	**0.99***	1.24	**0.98***	1.14	**0.85***	0.98	**0.84***	0.87	TmVeg (°C)
TnVeg (°C)	**0.63***	1.4	**0.95***	2.59	**0.65***	1	**0.72***	1.53	TnVeg (°C)
TxVeg (°C)	**0.81***	5.11	**0.48***	4.42	**0.52***	3.56	**0.64***	2.77	TxVeg (°C)
CNI (°C)	**0.95***	0.81	**0.87***	1.24	**0.85***	1.2	**0.85***	0.91	CNI (°C)
TnRest	**0.81***	0.76	**0.85***	1.99	**0.75***	2.14	**0.8***	1.17	TnRest
GSP (mm)	**0.64***	295.39	**0.74***	410.3	**0.5***	204.67	**0.55***	103.91	GSP (mm)
SprR (mm)	**0.91***	43.28	**0.77***	65.38	**0.68***	111.33	**0.84***	57.54	SprR (mm)
MON									
	SPHERA vs CPM		SPHERA vs RCM		E-OBS vs CPM		E-OBS vs RCM		
Index	ϱ	RMSE	ϱ	RMSE (°C)	ϱ	RMSE	ϱ	RMSE	Index
BEDD (GDD)	**0.92***	55.33	**0.91***	51.04	0.35	96.32	0.43	96.27	BEDD (GDD)
HI (GDD)	**0.86***	232.29	**0.94***	233.54	**0.82***	151.35	**0.72***	158.76	HI (GDD)
WI (GDD)	**0.93***	284.54	**0.93***	284.39	**0.45***	217.68	0.31	224.69	WI (GDD)
TmVeg (°C)	**0.93***	1.34	**0.92***	1.34	0.42	1.02	0.31	1.05	TmVeg (°C)
TnVeg (°C)	**0.69***	0.94	**0.77***	1.76	**0.67***	1.36	**0.62***	1.58	TnVeg (°C)
TxVeg (°C)	**0.75***	2.75	**0.83***	2.52	**0.86***	2.02	**0.82***	1.84	TxVeg (°C)
CNI (°C)	**0.97***	0.84	**0.95***	0.58	**0.49***	1.9	0.4	1.38	CNI (°C)
TnRest	**0.9***	1.43	**0.86***	1.09	**0.8***	1.94	**0.79***	1.58	TnRest
GSP (mm)	**0.48***	128.26	**0.49***	106.85	**0.71***	136.38	**0.71***	45.89	GSP (mm)
SprR (mm)	**0.84***	60.96	**0.82***	40.48	**0.75***	68.15	**0.81***	34.61	SprR (mm)

A trend analysis is conducted on climatic and productivity data as well as on bioclimatic indices. The presence of a trend may indicate the predominance of a long-term component of variability over the interannual component. The aim of the trend analysis is to identify when this occurs. In FRA the trend analysis reveals some positive statistically significant trends for temperature and temperature-based indices, especially in the E-OBS datasets, as also observed by Massano et al. (2023). Similar picture is found for the RCM, while for the CPM the only statistically significant and positive trend is for CNI. SPHERA reanalysis shows positive and significant trend for precipitation and precipitation-based index, that are not observed in the other series. For MON, the temperature trends are negative for E-OBS and positive for all other series except for TxVeg index computed with SPHERA. This is probably linked with the previously discussed misbehaviour E-OBS. Precipitation and GSP show a positive trend also in MON with E-OBS series. productivity data tested for trends, show that FRA has a significant positive trend in productivity while MON does not.

3.3.2 Bioclimatic indices control on wine grape productivity

3.3.2.1 *Single regression analysis*

A Spearman correlation analysis is performed to investigate the relation between the different bioclimatic indices and wine grape productivity and consequently determine the amount of total productivity variability (interannual and long-term) explained by these indices.

In FRA, the correlation coefficients are similar between climate simulations, observations, and reanalysis for the temperature-based indices, while diverge and are not significant for the precipitation-based ones (Figure 3.3-5). Few cases are statistical significance: CNI with model simulations, SPHERA, and E-OBS; the BEDD index only when RCM and E-OBS are used. In these cases, the long-term component of the total variability may be dominant, since BEDD, CNI, as well as the FRA productivity, have significant trends (Table A 8). RCM presents a statistically significant result also for TnRest, which does not show trend over the period 2000-2018. In this case, the interannual variability might be more relevant to explain productivity. The statistically significant coefficients are all positive indicating a positive effect on productivity of BEDD, CNI and TnRest.

In a previous study, conducted at regional scale using ISTAT productivity data and E-OBS (v26), Massano et al. (2023) did not find any statistically significant correlations for LOM neither with temperature-based nor precipitation-based indices. This indicates that working at a local scale is crucial to improve the portion of productivity variance explained by the bioclimatic indices, while the use of CPM for FRA does not provide any advantage compared to the RCM.

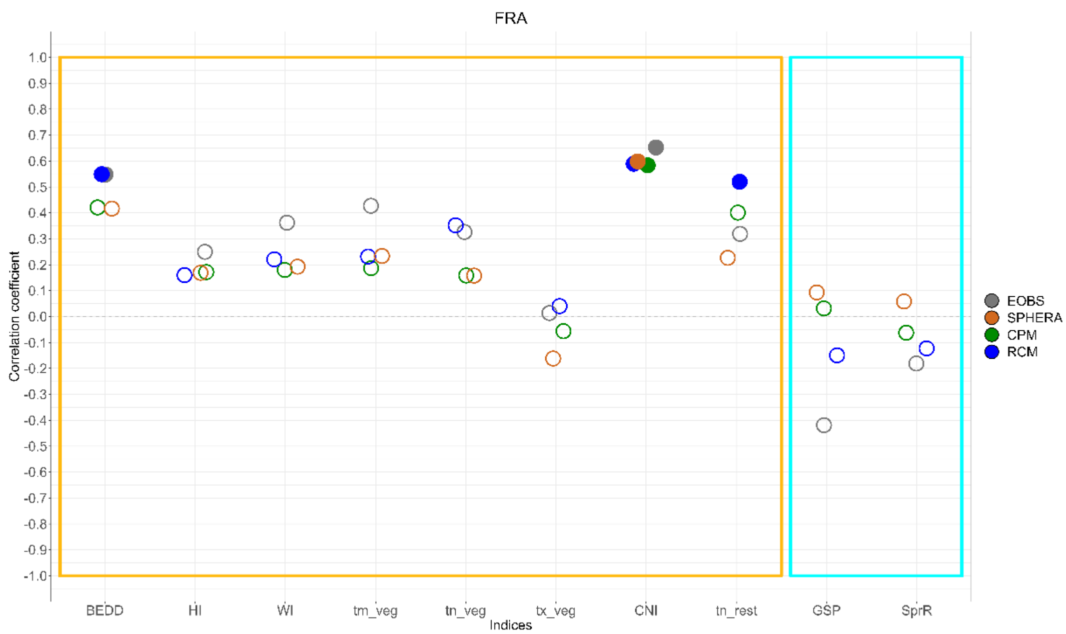


Figure 3.3-5: Spearman correlations coefficients between bioclimatic indices and wine grape productivity in FRA. Full colored circles indicate significant correlations (p<=0.05).

In MON, the correlation between productivity and bioclimatic indices are similar across all the datasets for BEDD, HI, WI and TmVeg but show greater variation for all other temperature-based and the precipitation-based indices (Figure 3.3-6). Significant results are found for TnVeg, only using CPM and for TxVeg in all datasets. To note that TxVeg displays a negative correlation, indicating that extreme temperatures during the growing period have a negative impact on production. This aligns with wine makers expectations and is partially supported by results from FRA (Figure 3.3-5), despite not being statistically significant. Both TnVeg and TxVeg indices show a significant positive trend (Table A 10), which suggests productivity being more sensitive to the long-term component of variability, at least for CPM.

Only the CPM simulation shows significant correlation for the precipitation-based index GSP. This could be linked to the more realistic representation of the precipitation field (Prein et al., 2015), although positive correlations with GSP are not typical, as an excessively wet season is usually detrimental to production. Thus, it is possible that other factors influence this correlation, such as specific viticultural practices or vintage management (Priori et al., 2019).

For example, harvesting immediately after rainfall may result in the collection of larger grapes, thus increasing the productivity. Additionally, specific trimming techniques can improve ventilation between the branches, reducing the risk of mould and fungus, and thus limiting the negative impact of precipitation on the harvest (Evers et al., 2010).

The MON case shows improvements compared to the analysis done with ISTAT data by Massano et al. (2023). In their analysis, TOS did not show any correlation between wine grape productivity and any bioclimatic indices, despite considering a longer time series. Being FRA and MON productivity data from the same population as the ISTAT productivity data (Table A 4 and Figure A 3), these results confirm that the use of the local scale can enhance the portion of productivity variability explained by the bioclimatic indices considered.

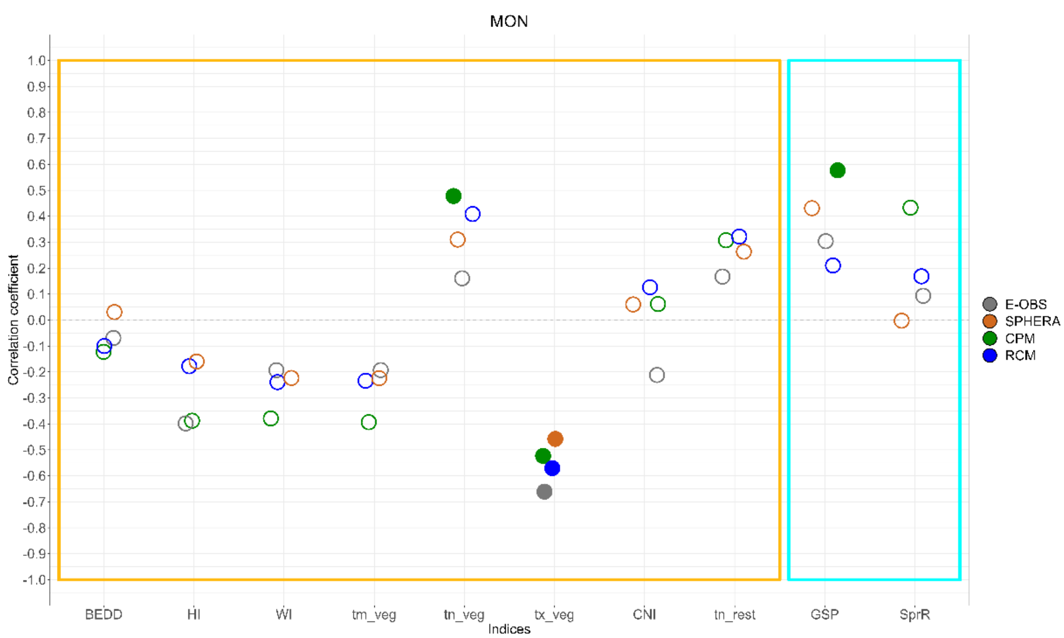


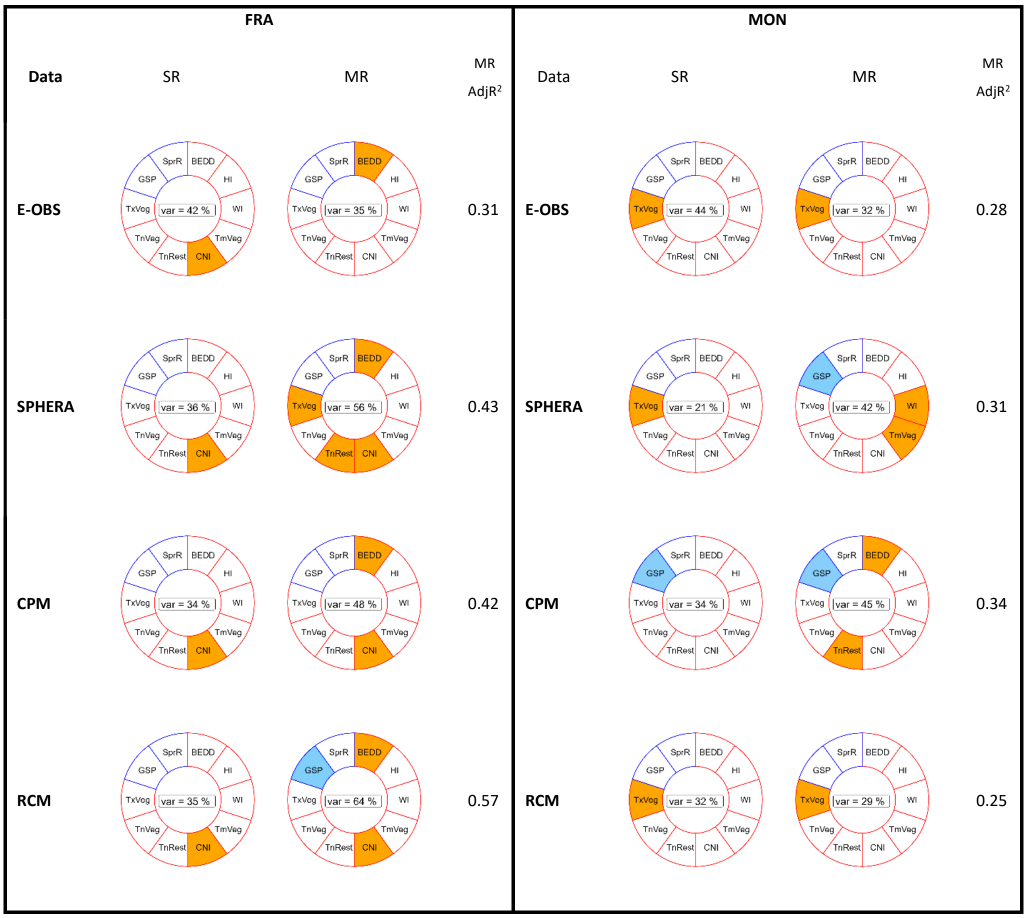
Figure 3.3-6: Spearman correlations between bioclimatic indices and wine grape productivity in MON. Full coloured circles indicate significant correlations (p<=0.05).

3.3.2.2 *Multi-regression analysis*

A multi regression (MR) analysis is carried out and compared with the single regression (SR) approach to see if considering a linear combination of bioclimatic indices increases the proportion of productivity variability explained by the indices.

Table 3.3.2 shows the results of the MR model, highlighting the selected bioclimatic indices and the variance explained in comparison with the SR method, for each case in both FRA and MON. To note that even when the MR selects just one index, this can differ from the single regression due to the algorithm chosen for the multi-regression (here K-fold Cross validation). The MR confirms that the temperature-based bioclimatic indices are more relevant than precipitation-based ones in explaining productivity variability, especially in FRA, where only for RCM the GSP is selected as a predictor. In MON, precipitation-based indices are selected as predictors in the MR model when using the CPM simulation and SPHERA reanalysis, confirming the relative higher importance of precipitation on productivity in this area compared to FRA. Thus, for MON, the improved representation of the precipitation field at convection-permitting scale could be a relevant factor, since in the other cases precipitation-based indices are excluded by the MR.

Table 3.3.2: Donuts chart indicating, for E-OBS, SPHERA, CPM and RCM, the best-performing index for the single regression (SR) and the indices included in the multi-regression model (MR), as well as the percentage of variance explained by each model (centre of the donut), in FRA and MON. Orange (blue) colour indicates temperature-based (precipitation-based) indices. The MR Adjusted R2 is expressed in the MR Adj R2 column.



The overview on the performance of the single-regression method (SR) and the multi-regression method (MR) is presented in Figure *3.3-7* show that using a linear combination of bioclimatic indices, i.e. MR, increase the proportion of explained total productivity variability, especially for FRA.

Overall, the bioclimatic indices explain a higher proportion of productivity variance in FRA compared to MON (Figure *3.3-7*a and Table A *12*), in line with previous findings at regional level for LOM and TOS (Massano et al., 2023). The highest proportion of explained variance in productivity is obtained in FRA with the MR approach and CPM data (64%), followed by

SPHERA (56%) and CPM (48%). The variance explained in MON is lower, with a maximum of 45% obtained for CPM and the MR approach, very close to SPHERA with MR (42%) and to E-OBS with SR (44%).

The maximum variance in productivity explained by the SR is compared with the MR variance (Figure 3.3-7b), demonstrating that the MR better represents productivity variability in FRA in all cases except E-OBS, which shows a slight decrease in performance (-7%). Meanwhile, SPHERA gains 20%, CPM 14% and RCM 29% with MR compared to SR approach. In MON, MR provides a better explanation for productivity variance in SPHERA reanalysis and CPM simulation, accounting for an increase of 11% and 21% respectively. However, for the E-OBS dataset and RCM simulation, MR performance decreases slightly (-12% and -3% respectively).

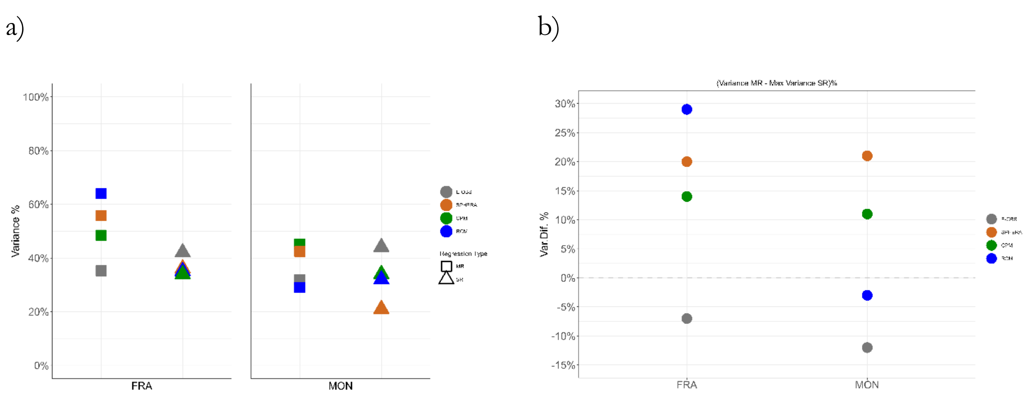


Figure 3.3-7: a) The maximum fraction of the wine grape productivity variance (%) explained by SR and MR in each consortium, the colour indicates the type of climatic data used, the squared (triangular) shape indicates the Muti – regressive (single regressive) approach. b) Variance differences in percentage between MR and SR for FRA and MON.

3.4 DISCUSSION AND CONCLUSION

The study assesses the potential of CPM to investigate the impact of climate variability on wine grape productivity at a local scale, using bioclimatic indices from the 19-year period 2000-2018. The CPM simulation is compared with RCM simulation, SPHERA reanalysis, and E-OBS observations. The study uses wine grape productivity data from two Italian wine consortia, namely 'Consorzio per la tutela del Franciacorta' (FRA) and 'Consorzio Del Vino Nobile di Montepulciano' (MON), to address some of the limitations identified by Massano et al., (2023). Specifically, the study aims to improve the quality of data and involve local businesses and stakeholders in impact studies. Single and multiple regression approaches are used to account for the possible interplay of bioclimatic indices in explaining wine grape productivity variability.

Overall, the single regression exhibits high values, but statistically significant results are only found in a small number of cases at the 95% confidence level. The multi-regression method consistently enhances the productivity variability explained by the bioclimatic indices and delivers optimal outcomes.

In FRA, the correlation coefficients are exclusively positive and statistically significant for temperature-based indices such as BEDD, CNI, and TnRest. There is a high degree of concordance between CPM and SPHERA reanalysis, which is considered as a reference in this study. Correlations with precipitation-based indices in FRA are not significant and tend to show negative relationships with productivity. The findings suggest that temperature is the main factor affecting production, while precipitation has a negative impact on productivity, potentially resulting in losses due to fungal diseases in the region.

The MON results indicate that only CPM provides statistically significant results for the precipitation-based index (GSP), which is positively correlated with productivity. Also, SPHERA, RCM and E-OBS in this region show positive correlations between precipitation-based indices and productivity, even if they are not significant. This differs from the observations in FRA, where the correlations are negative, even if not significant. However, it is worth noting that there are many differences in the geographical area and type of wine produced in FRA and MON. FRA is in the humid subtropical climatic zone, while MON is situated in the hot summer Mediterranean zone. Other factors, such as vintage management techniques and cultivar selection, can also influence productivity variability, in addition to climate. Investigation of these factors is beyond the scope of this paper. However, they can determine the positive effects of precipitation on productivity in MON. Meanwhile, the productivity for both FRA and MON exhibits a negative correlation with TxVeg with all the climatic data considered, but it is only significant for MON. This suggests that extreme maximum temperatures during the vegetative season (1st April - 30th October) have harmful effects.

These results, which are obtained at a local scale using data from consortia improve the previous studies conducted at regional scale by Massano et al. (2023). However, the use of the convective permitting model has a limited impact on the results of this study. The relevance of the CPM may not be immediately apparent in this context, as temperature is generally the main driver of wine grape production, and the added value of the CPM may be more appreciated when precipitation is a dominant factor.

The assessment presented can serve as a foundation for using CPMs in future impact studies, especially when convective precipitation is the dominant impact driver or when high-resolution climatic data is required. Moreover, it shows an application of the bioclimatic indices to wine grape productivity that is rarely used.

3.5 SUMMARY

In this chapter, the same methodology as in Chapter 1 is applied at the local scale, using different types of climate data: observations, reanalyses, regional climate model (RCM) and convection permitting model (CPM). In addition, three bioclimatic indices are added to the set used in Chapter 1. As for the time series, it is 19 years long and the analysis is carried out only on raw data in order to examine the long-term variability. The productivity data come from two Italian wine consortia, the 'Consorzio per la tutela del Franciacorta' (FRA) and the 'Consorzio Del Vino Nobile di Montepulciano' (MON). The single regression method only exhibits statistically significant results in a small number of cases at the 95% confidence level. However, the multiple regression method consistently improves the productivity variability explained by the bioclimatic indices and give optimal results. The comparison between RCM and CPM indicates that the use of the convection permitting model has a limited impact on the results of this study. In this context, temperature is generally the main driver of wine grape production, and the added value of the CPM may be more appreciated when precipitation is a dominant factor.

After examining the potential of bioclimatic indices to explain grape productivity variability at regional and local scales, the following chapter investigates the same issue using ecoclimatic indices calculated based on specific phenological phases instead of fixed calendar dates. This distinction may be important in the context of climate change that affects the phenological cycle of the grapevine. The analysis is carried out whit the observational dataset E-OBS at local scale over the FRA and MON area.

4.THE USE ECOCLIMATIC INDICES TO INVESTIGATE CLIMATE IMPACT ON WINE GRAPE YIELD AT LOCAL SCALE

Abstract

The impact of climate variability on wine grape yield is assessed using ecoclimatic indices tailored to the crop's specific life cycle stages during key phenological periods. These periods are selected through a validated phenological development model that accounts for various grape varieties. This study actively involves winegrowers and considers the unique characteristics of each study region, operating at a local scale with a focus on specific grape varieties. The yield data are provided by two Italian wine consortia, situated in Lombardia and Toscana, respectively. The ecoclimatic indices are correlated with grape yield data using single and multiple regression analyses. The study evaluates the different contributions of each ecoclimatic index to the yield formation process and quantifies the portion of total yield variability explained by these predictors, both individually and in linear combination. Given the limited existing literature on grapevine yield modelling, this paper introduces and discusses a set of ecoclimatic indices derived from current knowledge of climate's influence on grapevine development. Moreover, the methodology outlined here can be applied to future climate projections to investigate climate change and its potential impact on grape yield.

4.1 INTRODUCTION

Wine production, in quality and quantity, depends on a delicate balance between different climatic conditions: rainfall, sunshine, temperature, humidity, etc. (Laurent et al., 2021; Rienth et al., 2021). The development of the grapevine is mainly governed by air temperature, which determines the timing of the phenophase's interval, a key aspect to produce high-quality wine (Jones & Davis, 2000; Pearce & Coombe, 2004). Temperature is also the main factor that regulates the sugar content and flavour of the berry (Van Leeuwen, 2010; Van Leeuwen & Darriet, 2016). While drought can lead to a decrease in production, rainfall, especially in spring, can also trigger pests and diseases that affect grape production and the overall quality of the berry (Boso et al., 2014; Salinari et al., 2006). Although of primary importance, climate is not the only factor influencing grape quality and yield, the concept of terroir encompasses many other components, both environmental and cultural, such as soil characteristics and vineyard management practices (Bonfante et al., 2018; Spielmann & Charters, 2013). The link with terroir is strong in a country with a long-lasting wine growing tradition as Italy. In 2022, Italy was the world's leading wine producer, with 49.8 million hL, and the second-largest wine exporter, valued at 7.8 billion euros (OIV, 2022). Furthermore, Italy is considered a climatic hotspot (Cos et al., 2022), and climate change could potentially present a challenge to the wine industry.

Bioclimatic indices are a frequently used tool for evaluating the impact of climate on crops and crop yield. They are used to assess the suitability of a region for viticulture and are often linked to harvest dates to assess the impact of climate on vines development (Dalla Marta et al., 2010; G. C. Koufos et al., 2018). They are also used in conjunction with climate projections to study possible shifts in wine-growing areas due to climate warming (Moriondo et al., 2013; M. Santos et al., 2019). A different approach is proposed by Massano et al. (2023), who link bioclimatic indices to grape productivity data. The bioclimatic indices calculated on fixed calendar dates, also called agroclimatic indices, refer to theoretical occurrences of phenological phases. With global warming, the phenological timing is changing (Bernáth et al., 2021), which can limit the ability of agroclimatic indices to frame the impact of climate on crops, along with with the fact that they are not suitable for variety-specific studies (Moriondo et al., 2015). Another approach is the use of ecoclimatic indices, which are calculated based on the crop life cycle, during relevant phenological periods (Caubel et al., 2015). The ecoclimatic indices allow the characterisation of the climatic impact on crop growth and development, during the selected phenological period, or in days dedicated to specific cultural practices (harvest, pruning, etc). In this framework, crop models are essential to study the impact of climate on crops by integrating crop physiology with environmental conditions (Naulleau, Gary, Prévot, Berteloot, et al., 2022). This approach has been developed in numerous recent studies on cereal and other crops (Holzkämper et al., 2013; Le Gouis et al., 2020; Mkhabela et al., 2010), while recent works used ecoclimatic indices for studying the impacts of climate change on viticulture over French (Zito et al., 2023) and European (Sgubin et al., 2023) wine regions.

There are also numerous studies investigating the impact of climate on grapes, linking large-scale atmospheric patterns to grape phenology and quality (Dalu et al., 2013; Salinger et al., 2015) or the impact of climate change on harvest date (Di Lena et al., 2019; Lena et al., 2012).

These papers consider the suitability of grape production mixing the impact of climate on grape quality and quantity. While grape quality contributes strongly to wine industry revenue for premium wines, yield remains a driving factor for the economic viability of the wine industry

(Ashenfelter & Storchmann, 2016). The consequences of climate change have been however little considered. White et al., (2006) suggested that extreme heat might affect negatively yield in the western USA, without however supporting these analyses with field calibration. Fraga et al., (2016), used the crop model STICS adapted to grapevine to simulate various variables (LAI - leaf area index, grapevine water, and nitrogen status, yield) for the past 1980-2005 (climate data reanalysis) and future (21st century projection) periods in western Europe. Parametrization with a single cultivar (Pinot noir), yield simulations showed discrepancies with observations, as cultivar, training systems, and regulations strongly vary between European wine producing regions. To ensure accurate modelling, it is important to validate models using multiple cultivars due to variations in phenological timing. Additionally, it is important to consider different geographic areas during validation.

In this work, the impact of climate variability on grape yield is evaluated for two wine producing areas of Italy. Wine grape yield here indicate the amount of harvest collected per unit of surface area, expressed in either grape mass or wine volume units (Laurent et al., 2021). The areas considered are the Franciacorta wine region in Lombardia, northern Italy, and the Montepulciano area in Toscana, central Italy. The aim of this study is to better understand the relationship between climate and viticulture by linking ecoclimatic indices with grape yield data, to support the adaptation of the wine sector to climate change. This assessment uses phenological and water balance models to calculate ecoclimatic indices. The relationship between the ecoclimatic indices and grape yield data is explored by using both a single and a multiple regression approach. This research directly involves the winegrowers and considers the specificity of the areas of interest. The yield data are provided by two Italian wine consortia, 'Consorzio per la tutela del Franciacorta' (FRA) and 'Consorzio Del Vino Nobile di Montepulciano' (MON). The climatic data used as input in the model are obtained from the E-OBS gridded database of *in situ* observations. The use of the phenological development model allows the selection of the phenological periods more sensitive to the climatic conditions for each specific variety. Furthermore, to the best of the authors' knowledge, the here considered relationship between the ecoclimatic indices and grape yield in Italy has not been discussed in previous studies.

4.2 DATA AND METHODOLOGY

4.2.1 Yield data

The yield data used in this study are provided by two Italian wine consortia: 'Consorzio per la tutela del Franciacorta' (FRA), and 'Consorzio Del Vino Nobile di Montepulciano' (MON) (Figure *4.2-1*). The two consortia provided the area under vines in hectares (ha), the hectolitres produced (hl) and the maximum percentage of the grape yield to be converted into wine (70%). In this analysis, the hectolitres provided are converted into quintals (q) using the maximum percentage allowed, and then the yield (q/ha) is calculated by dividing the quintals of grapes by the vineyard area.

FRA, mostly known for sparkling wine, is a small (200 km^2) winegrowing region in Lombardia, northern Italy. The consortium currently maintains three designations: Sebino IGT, Franciacorta DOCG and Curtefranca DOC, that before 2011 was knew as Terre di Franciacorta (https://franciacorta.wine/en/). This work focuses on the denomination Terre di Franciacorta, the red wine (T.FRA.Red) from 1997 to 2010 (14 years) and the wite wine (T.FRA.White) from 1997 to 2009 (13 years) (Figure 4.2 2). The area's climate is influenced by Iseo Lake, located at the northern border, which tempers the heat of the plain in summer and protects the area from northerly cold advections during winter (Leoni et al., 2019).

MON territory is part of Toscana region in the centre of Italy. The consortium preserves three designations: Vino Nobile di Montepulciano DOCG, Rosso di Montepulciano DOC and Vin Santo di Montepulciano DOC. The area is characterized by a Mediterranean climate with hot and dry summers and mild and rainy winters (Costantini et al., 2013). The analysis is made on the aggregation of two denomination: Vino Nobile di Montepulciano DOCG, Rosso di Montepulciano DOC, for the period 1997-2019 (23 years), here indicated as MON.VN.R (Figure 4.2 2).

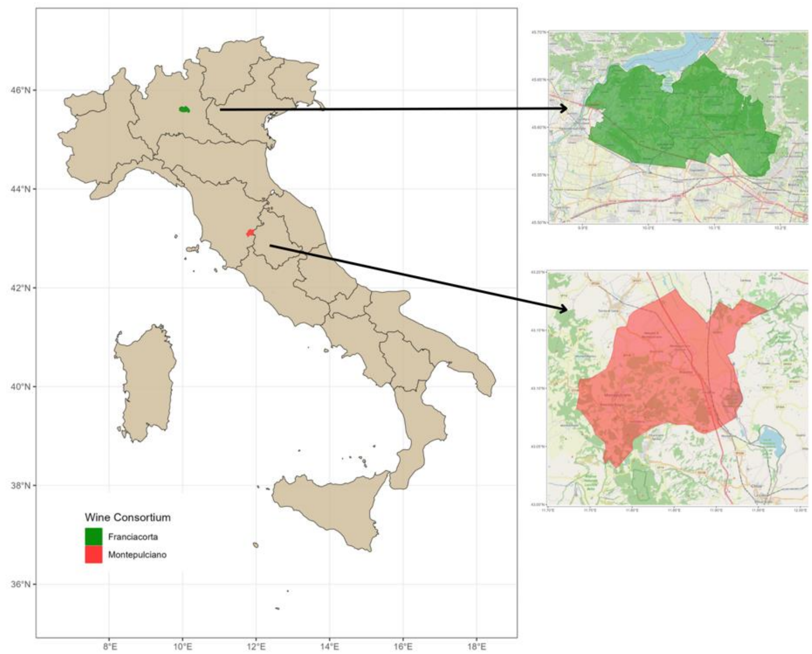


Figure 4.2-1: Study area

The MON consortium provided yield data from 1989 to 2019, but after an exploratory analysis of the yield series, the first 8 years (1989-1996) are excluded. The mean of the yield data from 1989 to 1996 is compared with the mean of the data from 1997 to 2019 and the results show significant differences in the mean (Figure A *4*, Figure A *5* and Table A *13*). A possible explanation lies in the variation in area observed in the data between the two periods (not shown), no further explanation or metadata is available from the Consortium. The authors decided to proceed with the analysis using the 1997–2019 time window.

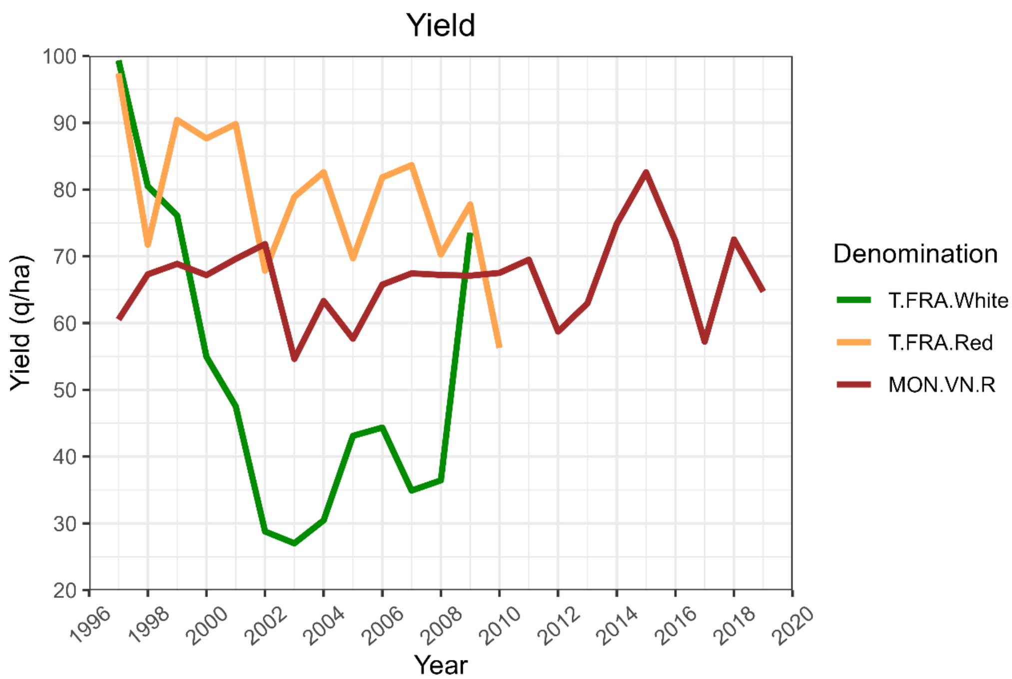


Figure 4.2-2: the plot shows yield time series for Terre di Franciacorta – White (T.FRA.White) and Terre di Franciacorta – Red (T.FRA.Red); MON.VN.R is the result of the aggregation of "Vino Nobile di Montepulciano" and "Rosso di Montepulciano".

4.2.2 Climate observation dataset E-OBS

The climatic data used in this study are extracted from the observational dataset E-OBS (v21), a gridded daily dataset covering Europe from January 1950 to the present day. The dataset was constructed using records from meteorological stations of the European National Meteorological and Hydrological Services (NMHSs) and other data holding institutions (Photiadou et al., 2017; Van Der Schrier et al., 2013). The horizontal grid resolution here used is 0.1 degrees in latitude and longitude, corresponding to approximately 11.1 km. The grid points of interest are selected based on the shape of the two consortia, and a weighted mean is calculated using the percentage of the grid point that overlaps the consortium area. The resulting climate data are then used as input to calculate ecoclimatic indices from phenological and water balance modelling. Daily reference evapotranspiration and solar radiation were calculated using Hargreves formulae (George H. Hargreaves & Zohrab A. Samani, 1985).

4.2.3 Phenological and water balance modelling and ecoclimatic indices

Climate potential impact on yield was assessed by estimating the consequences of temperature, rainfall, solar radiation, and soil water availability on various stages of the reproductive cycle of grapevine. Grapevine yield at harvest on year N is established by a series of stages, from the inflorescence primordia formation within latent buds during the middle of the previous growing season (N-1) to the berries' growth until harvest (Laurent et al., 2021; Li-Mallet et al., 2015). Growing season N-2 should also be considered, as it might affect grapevine vigour on year N-1, which is correlated with inflorescence primordia formation and the number of latent buds (Rives, 2000). The model considered here accounts only for N-1 and N.

The periods of interest were calculated from simulated grapevine phenological stages using the temperature related phenological modelling. *Budburst* (stage 07 on the BBCH scale, see Coombe, 1995) was calculated using the Smoothed-Utah/Wang & Engel model, as proposed and adapted to grapevine by Morales-Castilla et al. (2020), which accounts for cold effect on bud dormancy rise (starting on August 1st of the previous year) and heat positive impact on budburst occurrence. *Flowering* (BBCH65) and *veraison* (BBCH81) dates were calculated using the GFV - Grapevine Flowering Véraison model (A. Parker et al., 2013), which cumulates daily temperatures over 0°C from day of the year 60 (March 1st). *Harvest* (BBCH89) is not a phenological stage per se, as it is set by the grape grower or winemaker according to the type of sought product and the sanitary status of the grape. Harvest date has been estimated using the GSR – Grapevine Sugar Ripeness model (A. K. Parker et al., 2020), which cumulates daily temperatures over 0°C from day of the year 91 (April 1st) to simulate the date at which a given level of sugar level in grapes is reached. All three phenological models have been run using parameters adapted to grapevine varieties and sugar level at harvest adapted to each region (see Figure *4.2-3*). Here, the following key periods for yield formation process were considered and established by means phenological modelling (Figure *4.2-3*).

During year N-1:

- **GrowSeas**: the growing season period, from budburst (BBCH07) to harvest (BBCH89, here defined as "theoretical maturity", see below). A severe frost event during the growing season N-1, typically in Spring, is reported by grape growers to favour yield on the following year. This is the case in France for vintages 1981, 1991, 2017 and 2021 (frost) and 1982, 1992, 2018 and 2022 (high yield). The hypothesis that frosts damage enhances yield on the return crop has not been explored by scientific research. The potential impact of frost damage intensity was assessed through the utilization of a frost stress index, computed as the cumulative number of minimum temperatures falling below a specified threshold for each cold event occurring subsequent to budburst. While grapevine tissues after budburst can resist to temperature up to -2°C (Bois et al., 2023), here the threshold of +2°C was used based on the hypothesis that negative temperature are probably reached in some vineyards of the wine producing region when E-OBS climate data provide a value at 2°C or below.

- **Fertility**: a period starting 15 days before flowering (BBCH65) and lasting until 15 days before veraison (BBCH81), during which inflorescence primordia forms in the buds (Li-Mallet et al., 2015), i.e. "bud fertility". Mean and sum of solar radiation were considered during this period, because light intensity is a strong exogenous driver of bud fertility (Burrnose, 1970). When available soil water for grapevine falls below 40% of total soil water capacity, water deficit negatively affects bud fertility (Naulleau, Gary, Prévot, Berteloot, et al., 2022). The average relative soil water content, also called "fraction of transpirable soil water" (FTSW), was calculated using the water balance model proposed by Lebon et al., (2003) and described below.

During year N:

- **GrowSeas:** during the growing season of year N, the consequence of spring frost and extreme heat on yield were considered. Frost damage was assessed by the frost stress index as defined above. Extreme heat was considered as the sum of maximum temperatures over 35°C, a threshold above which sunburns can be observed on grapes (Hulands et al., 2014);
- **Postbudburst:** a 20-day period after budburst (BBCH07), during which cool temperature might reduce the number of inflorescences (Pouget, 1981). The average minimum temperature during this period was calculated.
- **Diseases:** corresponds to the period during which powdery and downy mildews, major grapevine diseases (Bois et al., 2017), are likely to occur. This period was set from budburst (BBCH07) to 15 days after full bloom (BBCH65), during which both climate conditions and grapevine sensibility are suitable for mildew epidemics (Gadoury et al., 2012; Gessler et al., 2011). During this period, the

hydrothermal index proposed by Branas et al. (1946) adapted by Fraga et al. (2013) was here modified as the cumulated product of average temperature and precipitation, under the hypothesis that warm and humid conditions favor the occurrence of diseases.

- **Harvest:** this period has been defined as covering 10 days before and 10 days after theoretical grape maturity (BBCH89, see below). During the fruit ripening period, rainfall might either favour grey mould (Molitor et al., 2016) or increase yield by increasing berry size. Consequently, the sum of precipitation during this period has been considered as an explaining variable for yield modelling.
- **Pollen:** coincides with the flowering-onset, which starts 5 days before full bloom (BBCH65) and lasts 15 days after. During this period, rainfall can wash out the pollen, failing fecundation. The sum of cumulated rainfall, as well as the average number of rainy days (precipitation > 1 mm), were considered. Rapid growth of the pollen tube is a determinant of ovary fertilization. Pollen tube growth is strongly governed by temperature (Staudt, 1982). The effect of temperature was assessed by calculating the average daily heat units during the *Pollen* period, using Wang and Engel's model (Wang & Engel, 1998) as adapted to grapevine by García de Cortázar-Atauri et al. (2010).
- **FloMat** corresponds to the period between flowering and maturity (BBCH65 - BBCH89) during which the fruit develops. During this period, water deficit strongly affects yield (Gambetta et al., 2020). Grapevine water status was assessed through an average water deficit stress index, defined as 1 minus the grapevine's relative stomatal conductance estimated from the water balance model proposed by Lebon et al. (2003) and described below.

Grapevine water status has been simulated using Lebon et al. water balance model (Lebon et al., 2003). Two outputs provided by the model have been considered. The first output is the fraction of transpirable soil water, which consists of the ratio between available soil water (ASW) and the total transpirable soil water (TTSW). TTSW varies strongly according to plant root system and soil physico-chemical characteristics. Here, it has been set at 150 mm. The second output is grapevine relative stomatal conductance (isv), which expresses the degree of stomata "openness" directly related to FTSW, using the relationship proposed by Pieri & Gaudillere, (2005). When isv = 1, stomata are closed, hence hydric stress is maximum. When isv = 0, stomata are open, hence there is no water deficit.

The water balance model separates grapevine transpiration and soil evaporation according to solar radiation interception by grapevine canopy. Radiation interception has been estimated using Riou et al. (1989) geometrical model that simplifies the grapevine row canopy as a parallelepiped. Grapevine canopy growth has simulated a linear relationship between the growth of the row (vertical, horizontal, and canopy porosity) and growing degree days over 10°C, from budburst (BBCH07) to 15 days after full bloom (BBCH65). Row azimuth was set to 0° (rows oriented South to North for all considered regions) and minimum porosity was set to 0.25 (25% of gaps in the canopy). Row maximum height, maximum width, and distance between rows were set to 1, 0.4, and 2 meters, respectively.

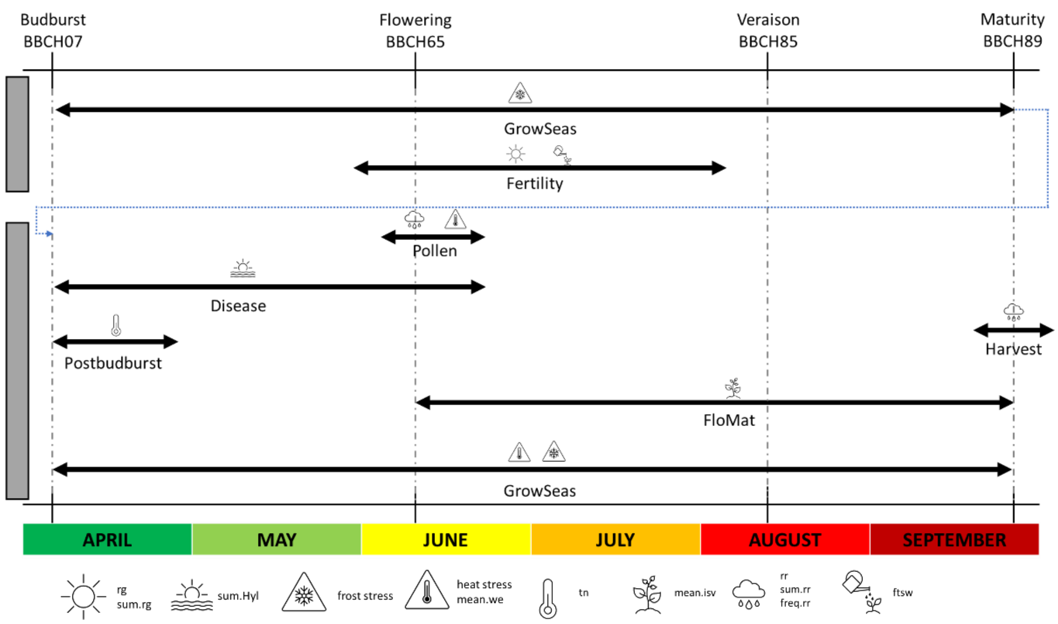


Figure 4.2-3: Scheme of the periods of interest for the computation of indices. The icons serve as a schematic representation of the ecoclimatic indices.

This work focuses on seven different periods, over which 13 ecoclimatic indices are computed by the agro-model. These indices, defined above and summarized in

Table 4.2.1, are considered the most relevant to assess the impact of climate variability on winegrape yield. As mentioned above, vines are perennial plants whose productivity is influenced by the climatic conditions of the years leading up to a specific harvest. To account for this effect, 4 of the 13 indices are based on the previous year (N-1), while the remaining 9 are based on the current year (N) of the harvest under investigation.

Table 4.2.1: list of ecoclimatic indices and their definitions. The orange (blue) background indicates an expected positive (negative) correlation with yield.

Year	Period	Index	Detail	COD.
N-1	*Fertility*	sum.rg	The sum of solar radiation during the period "fertility" (year N-1)	eco1.N-1
N-1	*Fertility*	rg	Mean of solar radiation during the period "fertility" (year N-1)	eco2.N-1
N-1	*Fertility*	ftsw	Fraction of Transpirable Soil Water average during the period "fertility" (year N-1)	eco3.N-1
N-1	*GrowSeas*	frost.stress.index.mThresN1	The sum of minimum temperature below a fixed threshold (year N-1)	eco4.N-1
N	*GrowSeas*	frost.stress.index.mThres	The sum of minimum temperature below a fixed threshold (Thres = 2 °C)	eco5.N
N	*GrowSeas*	heat.stress.index	The sum of maximum temperature above 35 °C	eco6.N
N	*Pollen*	sum.rr	The sum of precipitation during the period "pollen"	eco7.N
N	*Pollen*	freq.nrr1	The number of rainy days (rain > 1 mm) during the period "pollen"	eco8.N
N	*Pollen*	mean.WE	Average of Wang and Engel daily heat units adapted by provided in García de Cortázar-Atauri et al., (2010) during the period "pollen"	eco9.N
N	*Disease*	sum.HyI	The Hydrothermal Index modified from Branas (1946) as the product of the sum of daily precipitation per the average daily temperature during the period "pollen"	eco10.N
N	*Harvest*	sum.rr	The sum of precipitation during to harvest	eco11.N

N	*FloMat*	mean.isv	The mean relative stomatal conductance, an indicator of hydric deficit (water deficit related stress is maximum when isv = 0)	eco12.N
N	*Postbudburst*	tn	Average minimum temperature after post-budburst	eco13.N

4.2.4 Computation of eco-indices and parameters analysis

In this work, two geographical areas are considered, i.e. FRA and MON, and three denominations are analysed (T.FRA.White, T.FRA.Red, MON.VN.R). Those choices are determined by the data availability.

FRA provided data on the denominations Terre di Franciacorta Rosso (T.FRA.Red) and Terre di Franciacorta Bianco (T.FRA.White). According to the information provided by the consortia, the varieties authorised by the denomination laws are Chardonnay, for the white wine, Cabernet Sauvignon, and Merlot for the red (Figure *4.2-4*).

MON.VN.R is mainly made with Sangiovese grapes (at least 70%), while the remaining 30% can be made with other red grapes authorised for harvesting in Toscana. As previously described, the agro-model can be tailored to better suit the requirements of the case study. The Sangiovese variety is not available in the agro-model, so the simulation for MON.VN.R uses Merlot, Syrah, and Cabernet Sauvignon, which are allowed in Toscana and are agronomically similar to Sangiovese (Palliotti et al., 2018)(Figure *4.2-4*).

The yield data refer to specific denominations that are a mix of more types of grapes, for this reason, a sensitivity analysis of the model to the “cultivar” and “maturity sugar content” parameters is performed.

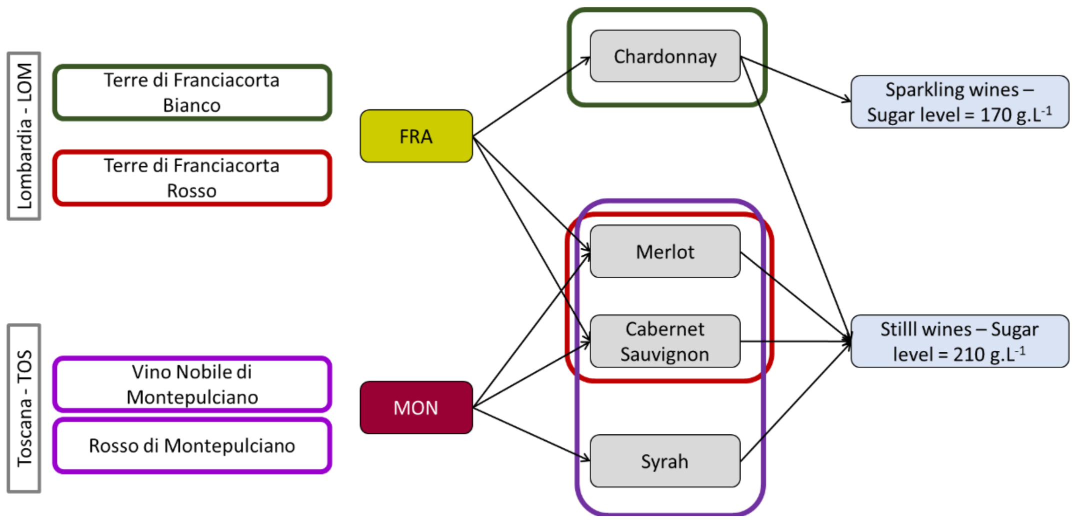


Figure 4.2-4: Scheme of the grape varieties considered in the study. From the left side there are the two geographic regions of interest, followed by the respective denomination provided by the consortia (FRA and MON). The last two column indicates which variety (Chardonnay, Merlot, Cabernet Sauvignon and Syrah) and which sugar content is used to set the agro-model.

4.2.5 Correlation with yield data

After the sensitivity analysis, the ecoclimatic indices computed by the agro-model are correlated (Spearman method) with yield data to investigate their possible relationship. In FRA the ecoclimatic indices obtained running the agro-model using Chardonnay 170 g*L^{-1} is correlated with T.FRA.White yield data, while the indices obtained for FRA using Merlot and Cabernet Sauvignon are correlated whit T.FRA.Red. For the MON area, the correlation is computed for MON.VN.R, for each of the varieties considered (Figure *4.2-4*).

To consider the interplay that the different indexes can have on wine production, a multivariate analysis is conducted. Multiple regression linear models are elaborated by combining up to 3 ecoclimatic indices as predictors to explain the yield of each series (Harrell et al., 1984). All possible combinations are tested, and each model performance is assessed by leave-one-out cross-validation (LOOCV): one year of the yield series is iteratively removed to elaborate a training data set from a multiple linear regression model is fitted and then the yield is predicted for the year that has been removed. Once this cross-validation has been performed for each year of the series, predicted data are compared to observed data calculating the model efficiency (Nash & Sutcliffe, 1970). Finally, the model providing the lowest efficiency to predict yield is selected.

4.3 RESULT AND DISCUSSION

4.3.1 Parameters analysis of phenological model

The ecoclimatic indices are computed in the FRA (Figure *4.3-1*) and MON (Figure *4.3-2*) areas using different settings. For the variety Chardonnay in FRA (white), two different values for the sugar content at maturity are tested (170 gL^{-1} for sparkling wines and 210 $g*L^{-1}$ for still wines), the differences between them are shown in Figure *4.3-1* for the eco11.N and eco12.N indices (black and green lines). Using lower sugar content in the GSR model (170 $g*L^{-1}$), the simulated harvest date is closer to that given by the consortium, usually around 15 August, than using 210 $g*L^{-1}$. This result is consistent with the fact that sparkling wines are mostly produced with the appellation Terra di Franciacorta white, in the period considered. Simulation for Chardonnay with 210 $g*L^{-1}$ sugar content at maturity is therefore excluded from further analysis. Meanwhile, the simulations for the varieties Cabernet Sauvignon and Merlot in FRA are carried out with the sugar content at maturity set at 210 $g*L^{-}$1 and included in the second part of the analysis. The variety harvested in MON area is Sangiovese, a cultivar not available in the budburst model (from Morales-Castilla et al., 2020), thus the parameters analysis is made with Cabernet Sauvignon, Merlot and Syrah (Figure *4.3-2*) that are similar to the Sangiovese vines, from an agronomic point of view.

For both areas (FRA and MON), the differences between the varieties are observed in eco4.N-1 and eco5.N, related to frost stress in years N-1 and N, and eco6.N, related to heat stress in year N. The other two indices that differ the most are eco11.N and eco 13.N, related to rainfall close to harvest and minimum temperature after bud burst, respectively. Frost and heat days are calculated between budburst and harvest. Frost simulated potential damage (frost stress index) depends on phenological features of budburst, that change between varieties: from 0 to 15 days between Chardonnay, the earliest variety used here, and Cabernet-Sauvignon, the latest variety in FRA (and 0-14 days in MON) (as observed in our simulations and confirmed by phenological earliness reported in the French catalogue of Grapevine Varieties www.plantgrape.fr). Hence, a difference in frost stress index according to the variety was expected and is in line with a previous comparison of grapevine sensitivity frost risk estimation using phenological modelling (Bois et al., 2023). It is also the case for minimum temperature following budburst (eco13.N index). The larger sensitivity of the heat stress index to cultivar phenological parameters suggests that varieties reaching maturity earlier (and harvested earlier) might avoid heat waves occurring in the late summer at the end of August or in September. As harvest dates might vary significantly according to variety and sugar level at which grapes are considered ripe (170 or 210 $g*L^{-1}$), eco11.N (rainfall close during *harvest* period) changes dramatically. As highlighted by (Bécart et al., (2022), the ideal conditions for grape ripening are expected to change in response to rising temperatures, hence the need to consider ecoclimatic indices calculated close to harvest. They also highlight the importance of characterising the intermediate phenological stages that can play an essential role in the yield formation process.

Figure 4.3-1: for FRA area, time series of the ecoclimatic indices computed with phenological parameters set according to each variety.

Figure 4.3-2 for MON area, time series of the ecoclimatic indices computed with phenological parameters set according to each variety.

4.3.2 Ecoclimatic indices and yield data correlations

4.3.2.1 *Single regression approach*

The Spearman correlation is computed on a subset of cases selected based on the parameters analysis. For the FRA area, the yields of the T.FRA.White denominations are correlated with the ecoclimatic indices calculated with Chardonnay (170 g*L^{-1}) for the period 1997-2009. Meanwhile, the yield data of the T.FRA.Red denominations are correlated with the ecoclimatic indices calculated with Merlot and Cabernet-Sauvignon for the period 1997-2010. For the MON area, the yield data of MON.VN.R for the period 1997-2019 are correlated with the ecoclimatic indices calculated for the varieties Merlot, Cabernet Sauvignon, and Syrah (Figure *4.2-4*).

The eco3.N-1 (average fraction of transpirable soil water, FTSW, during fertility period on year N-1) shows a significant correlation ($p < 0.04$) with the grape yield for the denomination T.FRA.White Chardonnay (Figure *4.3-3*). The positive relationship between eco3.N-1 and the yield is consistent with observations made between FTSW and yield in South of France (Naulleau et al., 2022), as water deficit during latent bud formation (*fertility* period) leads to the formation of fewer grapes during the following year. The study conducted by Yang et al., (2022) investigated the impact of water stress on yield loss in various European wine regions, including in Italy, focusing on the phenological period between flowering and veraison, which is not considered in this work. However, their results align with what is shown here, namely that higher water stress leads to higher yield loss. For the second denomination used in FRA, T.FRA.Red, significant, and positive correlations are observed for the eco5.N index (frost risk index on year N) with both varieties tested ($p < 0.03$ for both varieties) (Figure *4.3-4*). This is unexpected because frost risk in the year N is supposed to damage yield. Eco5.N exhibits however null values for most of the considered vintages except for 1997, 2003, and 2007. In 2003 for Merlot and 2007 for Cabernet Sauvignon, eco5.N was very high, indicating a binary behaviour (it zero or ten for Merlot) of this ecoclimatic index, not observed for MON, and it is possible that these values are driving significant Spearman coefficients.

For MON.VN.R, eco7.N, eco8.N and eco10.N (Figure *4.3-5*) are positively correlated with yield for all the variety tested. The eco7.N index is the sum of precipitation during the *pollen* period, which can be detrimental to yields because the pollen is washed away by rain and fewer flowers are fertilised, phenomenon also known as coulure. The eco8.N describes a similar phenomenon of coulure but accounts for the frequency of rainfall during the period *pollen*. The hydro-thermal index (eco10.N) is a combination of the rate of rainfall and the temperature during the growing season to determine the risk of downy mildew to the grapevine (Branas et al., 1946; Tonietto

& Carbonneau, 2004). Therefore, a high value of eco10.N indicates a high risk of disease occurrence in the vines, that can lead to a lower yield. Thus, a negative correlation was expected while positive ones are observed for all three indices. The climatic conditions of the area, which are hot and dry (Fratianni & Acquaotta, 2017), may be responsible for the unexpected positive correlations between yield and eco7.N, eco8.N, and eco10.N indices. This implies that, in an area where rainfall is usually scarce, precipitation can have a positive impact on yield, and a dry area may be less susceptible to fungal disease. Indeed, a positive correlation have been found during fruit development on the berry weight of the Grenache variety with humidity and rainfall frequency in the semi-arid Southern Rhône area in France (Bécart et al., 2022).

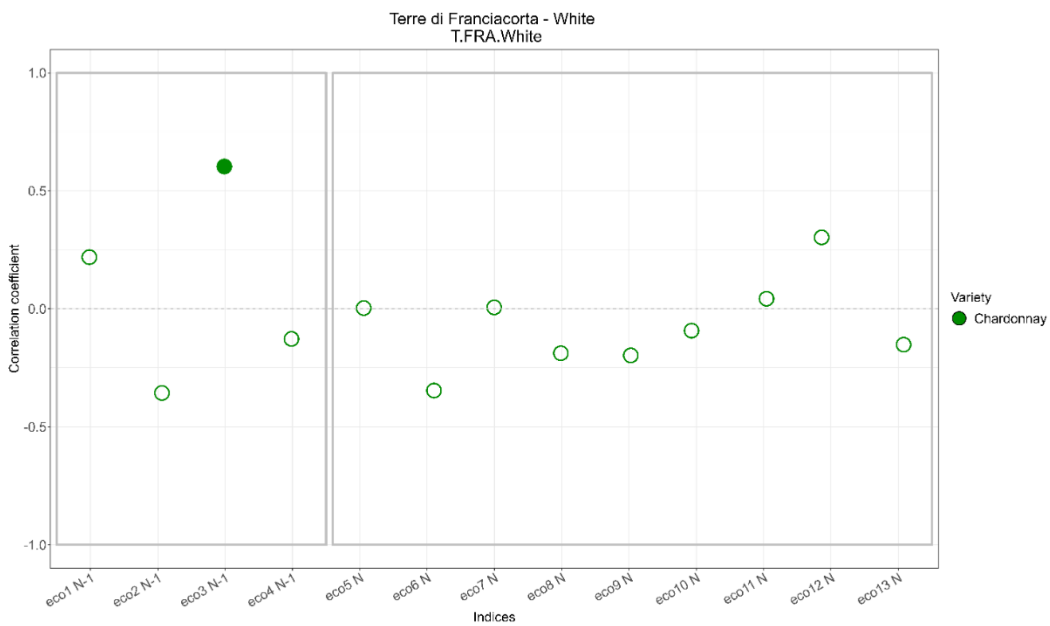


Figure 4.3-3: T.FRA.White, correlation coefficients between grape yield and ecoclimatic indices. Full circle represents statistically significant results (p<=0.05).

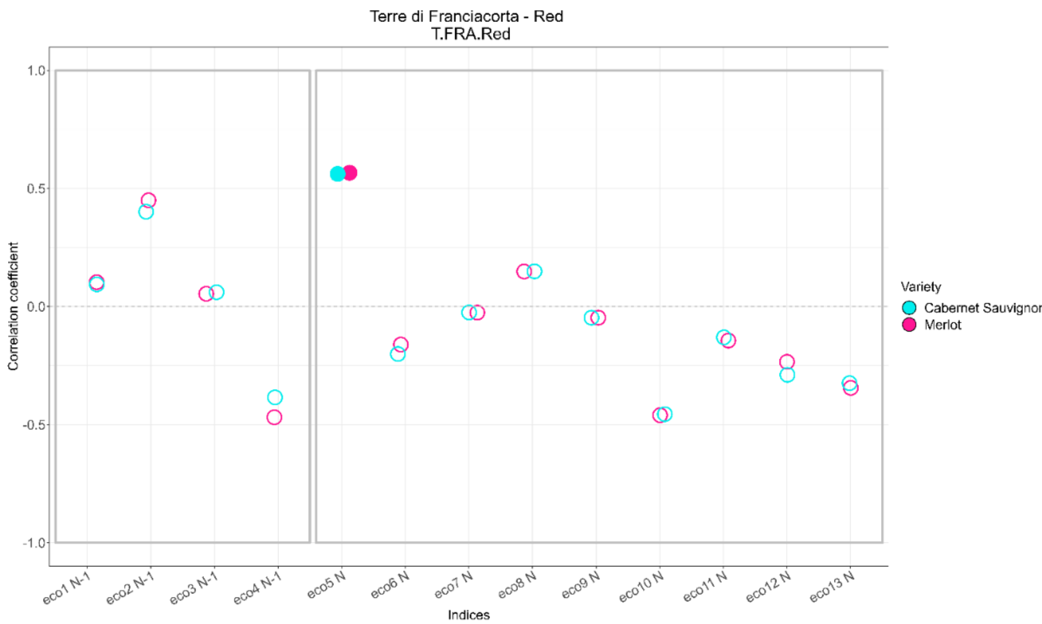


Figure 4.3-4: T.FRA.Red, correlation coefficients between grape yield and ecoclimatic indices. Full circle represents statistically significant results (p<=0.05).

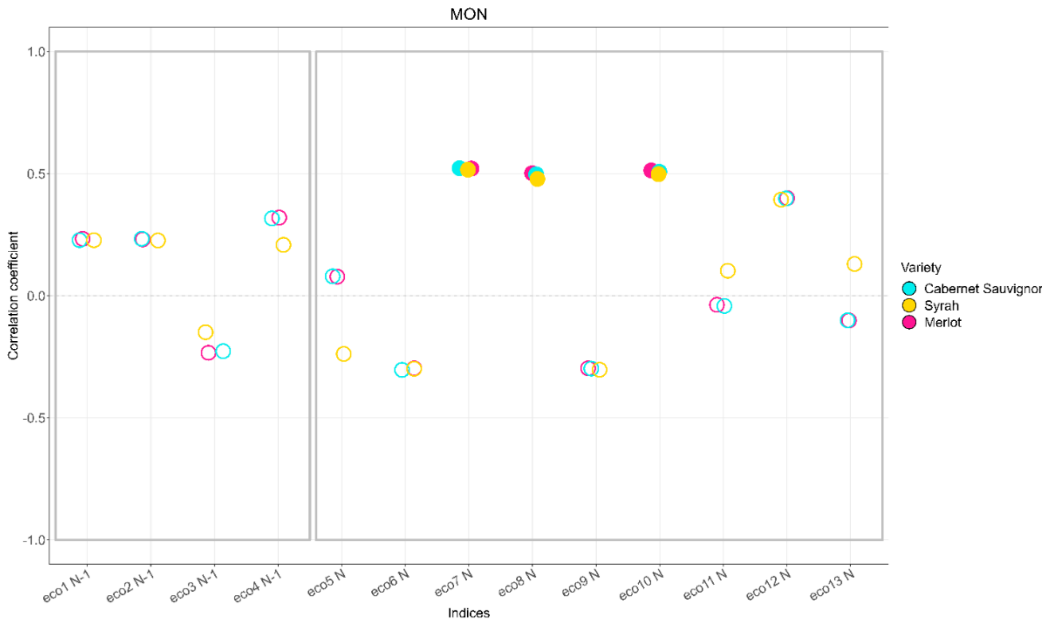


Figure 4.3-5: MON.VN.R, correlation coefficients between grape yield and ecoclimatic indices. Full circle represents statistically significant results (p<=0.05).

4.3.2.2 *Multi regression approach*

Because yield formation is the results of the combination of climate conditions at various stages of grapevine reproductive cycle, multiple linear regression modelling combining up to three variables has been tested. The methodology adopted here is similar to that of J. A. Santos et al., (2011), who used a multivariate linear regression model to build a statistical grapevine yield model. However, they used only temperature and precipitation monthly data, whereas here, ecoclimatic indices are used to conduct more comprehensive work. The multi-regressive model's performance is compared to the single regression approach. The adjusted Pearson's determination coefficient R^2 between observed and predicted yield (by means of leave -one-out crosse validation procedure), is computed, and the variance explained by the model is compared with the maximum significant variance obtained with the single regression approach (Table 4.3.3) (Massano et al., 2023).

Table 4.3.1: predictor and coefficients of the multi-regressive model for T.FRA.White and T.FRA.Red. In the firs column are reported the denomination and the period considered, in the second column there are the variety and the Adjusted R squared. In the remaining column are reported the predictor of the model and their coefficients.

T.FRA.White	CHARDONNAY	Int.	ftsw - *Fertilty* (eco3.N-1)		
1997-2009	Adj. R^2 =0.44	5.72	80.55		
T.FRA. Red	MERLOT	Int.	heat.stress.index - *GrowSeas* (eco6.N)	mean.isv - *FloMat* (eco12.N)	tn - *Postbudburst* (eco13.N)
1997-2010	Adj. R^2 =0.58	136.62	-1.61	-48.99	-3.54
T.FRA. Red	CABERNET SAUVIGNON	Int.	sum.Hyl – *Disease* (eco10.N)	sum.rr - *Harvest* (eco11.N)	tn - *Postbudburst* (eco13.N)
1997-2010	adr. R^2 =0.56	128.73	-0.01	-0.09	-3.39

Table *4.3.1* shows the coefficients of the multi regression, and the corresponding adjusted R^2, for T.FRA.White for Chardonnay and T.FRA.Red for Merlot and Cabernet-Sauvignon. For T.FRA.White (Figure *4.3-6*), the multi-regressive model selected through the LOOCV criterion leads to the selection of only one variable: eco3.N-1, i.e. the fraction of transpirable soil water during the previous year (N-1), which has a positive coefficient, suggesting a positive influence on yield. The same result has been obtained with the single regression analysis. The predicted data are compared to the observed data in Figure *4.3-6* b, and they show good agreement, explaining up to 32 % of the series variance (Table 4.3.3). The year 2003 is predicted to have a higher yield than observed. This difference may be due to spring frost and heat related damage. In 2003, frost and heat stress indices are high (ecoclimatic indices eco5.N et eco6.N in Figure 4.3-1, respectively) suggesting indeed potential negative impact on grape production.

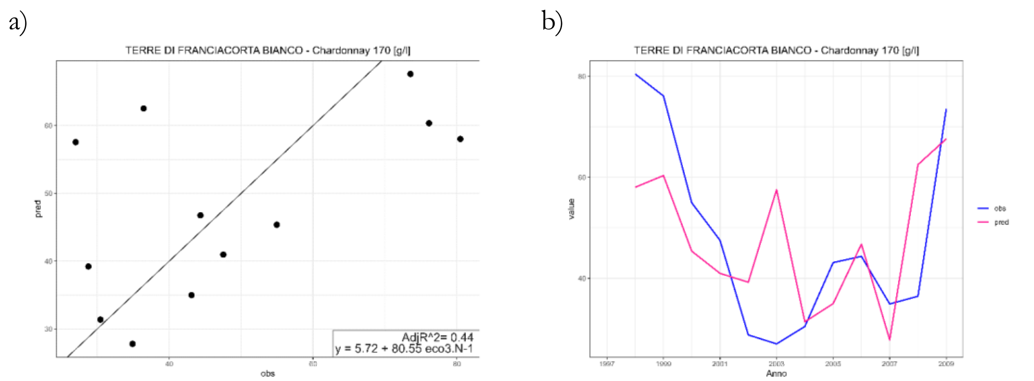


Figure 4.3-6: T.FRA.White – Chardonnay 170 g*L-1 1997-2009, panel a) scatter plot of predicted vs observed yield, panel b) time series of predicted (pink) and observed (blue) yield.

The predictor selected for the T.FRA.Red denomination used with Merlot variety (Figure *4.3-7*) are eco6.N, eco12.N, and eco13.N, all with negative coefficients. The eco6.N index represents the heat stress during year N, and a negative coefficient suggests that extreme heat leads to reduced yield, which is fully consistent with data reported from a large survey after strong heat waves in Australia (Webb et al., 2009). Eco13.N is the minimum temperature after budburst. The literature concerning the effect of temperature on flower differentiation on grapevine (Pouget, 1981) reported, for Merlot and Cabernet-Sauvignon, a clear positive effect of low temperatures (12°C) after budburst on the total number of flowers carried by vines, compared to high temperature (25°C). The negative coefficients observed for eco13.N support these observations. On the other hand, the eco12.N index represents the mean stomatal conductance. A low value indicates higher stress on the plants, which leads to lower yields. Therefore, a positive correlation is expected in this case, but a negative one is obtained here, suggesting that water deficit favours higher yield. Similar results are obtained for the Cabernet Sauvignon variety (Figure *4.3-8*), where the selected predictors are eco10.N, eco11.N and eco13.N, all of which have negative coefficients. The hydrothermal index eco10.N is related to the risk of disease, which has a negative impact on yield. Eco11.N represents the accumulated rain close to harvest time, which can trigger a grey mould infection resulting in less yield. Lastly, as for the case of Merlot, the eco13.N the negative coefficient observed in the model for Cabernet-Sauvignon suggests a negative impact on yield of increasing minimum temperatures around budburst, possibly though the number of produced flowers, as explained above.

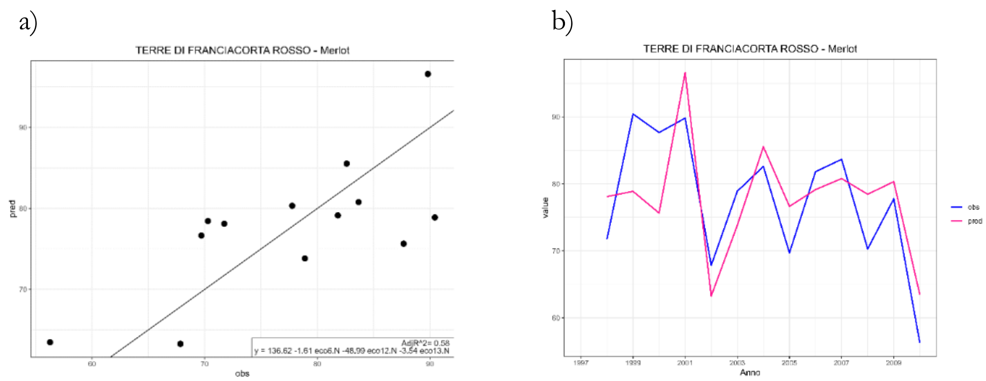


Figure 4.3-7: T.FRA.Red– Merlot 1997-2010 panel a) scatter plot of predicted vs observed yield, panel b) time series of predicted (pink) and observed (blue) yield.

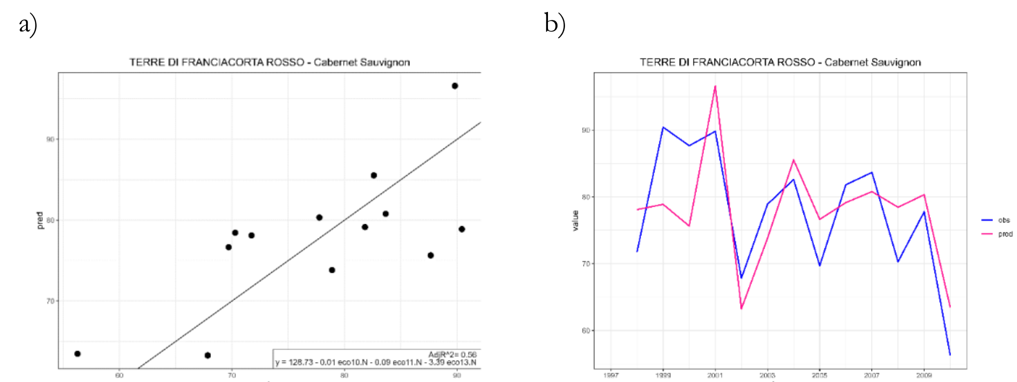


Figure 4.3-8: T.FRA.Red – Cabernet-Sauvignon 1997-2010 panel a) scatter plot of predicted vs observed yield, panel b) time series of predicted (pink) and observed (blue) yield.

Regarding the area of MON, the results obtained from the multi-regression analysis for MON.VN.R confirm those obtained from the single regression analysis (Figure *4.3-5*).

Table 4.3.2 shows the coefficients and Adj. R^2 of MON.VN.R for the tree varieties selected.

Table 4.3.2: predictor and coefficients of the multi-regressive model for MON.VN.R. In the first column are reported the denomination and the period considered, in the second column there are the variety and the Adjusted R squared. In the remaining column are reported the predictor of the model and their coefficients.

MON.VN.R	CABERNET SAUVIGNON	Int.	sum.Hyl – *Disease* (eco10.N)	mean.isv - *FloMat* (eco12.N)	frost.stress.index.mThresN1 – *GrowSeas* (eco4.N-1)
1997-2019	Adj. R^2 =0.37	50.52	0.01	30.88	0.21
MON.VN.R	MERLOT	Int.	sum.rg – *Fertilty* (eco1.N-1)	sum.Hyl – *Disease* (eco10.N)	mean.isv – *FloMat* (eco12.N)
1997-2019	Adj. R^2 =0.37	26.40	0.05	0.01	30.27
MON.VN.R	SYRAH	Int.	sum.Hyl – *Disease* (eco10.N)	tn – *Postbudburst* (eco13.N)	frost.stress.index.mThresN1 – *GrowSeas* (eco4.N-1)
1997-2019	Adj. R^2 =0.39	49.14	0.01	33.39	0.24

When using Cabernet Sauvignon parameters for phenological modelling, the multi-regressive model's Adj. R^2 value is 0.37, suggesting limited predictive ability (Figure 4.3-9). The selected indices are eco10.N, eco12.N, and eco4.N-1, all with positive coefficients (**Table 4.3.2**). The index related to disease risk (eco10.N) is expected to be negatively related to yield as confirmed by Fraga's (Fraga et al., 2014) logistic model in Portugal (Fraga et al., 2014). However, in this case, the coefficients show a positive relationship. This may be due to the dryness of the area, as discussed in the single regression analysis section. The coefficients for eco12.N (mean relative stomatal conductance during the *FloMat* period) and eco4.N-1 are positive, as expected since high values of the former indicate low deficit water, and the latter frost stress in the previous year (N-1), which leads to good yield in the following year, as empirical observations show. When using Merlot, the multi-regressive model has again an adj. R^2 value of 0.37 (Figure 4.3-10. The selected indices are eco1.N-1, eco10.N, and eco12.N, all with positive coefficients (Table 4.3.2). As previously discussed for Cabernet-Sauvignon, the hydrothermal index (eco10.N) is expected to have a negative coefficient. The sum of solar radiation during the fertility period in year N-1 (eco1.N-1) and mean relative stomatal conductance during fruit development and ripening *FloMat* period (eco12.N) are expected to have a positive impact on yield, as captured by the positive coefficient of the multi-regressive model (Table 4.3.2). The multi-regressive model produced similar results for the Syrah variety, selecting the predictors eco10.N, eco13.N, and eco4.N-1 (Figure 4.3-11). The positive coefficient of eco4.N-1 is expected since frost stress in N-1 can led to a good yield in year N, while the positive coefficients of eco10.N and eco13.N, although confirming previous results, are not expected. The counterintuitive result may be due to the hot and dry climate of the area, as already underlined previously.

a) b)

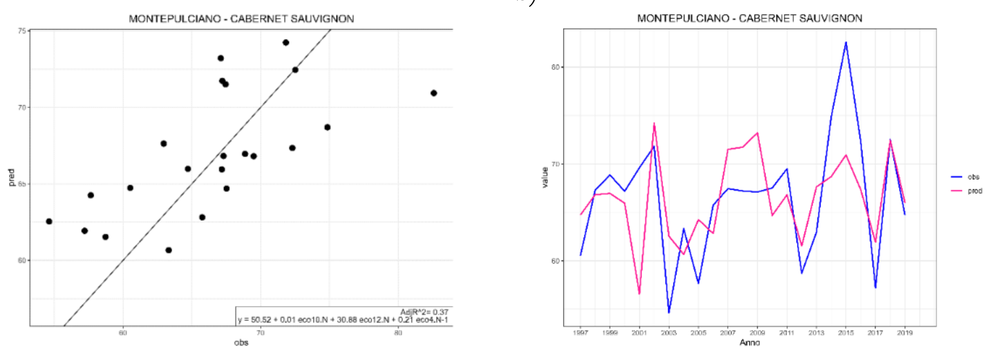


Figure 4.3-9: MON.VN.R - Cabernet-Sauvignon 1997-2019 panel a) scatter plot of predicted vs observed yield, panel b) time series of predicted (pink) and observed (blue) yield.

a) **b)**

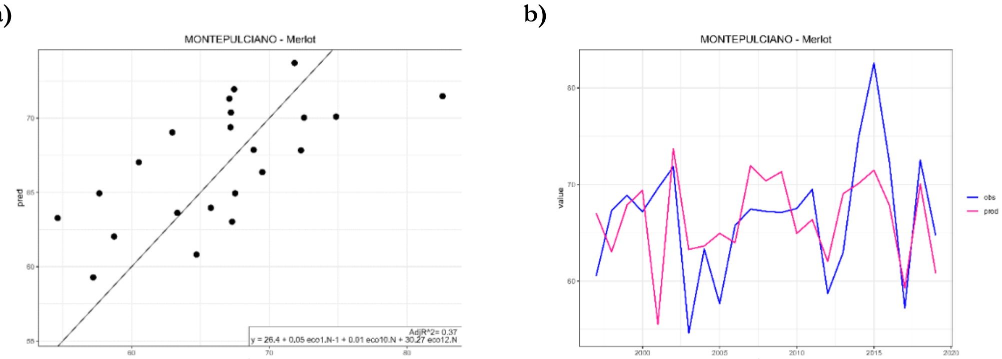


Figure 4.3-10: MON.VN.R - Merlot 1997-2019 panel a) scatter plot of predicted vs observed yield, panel b) time series of predicted (pink) and observed (blue) yield.

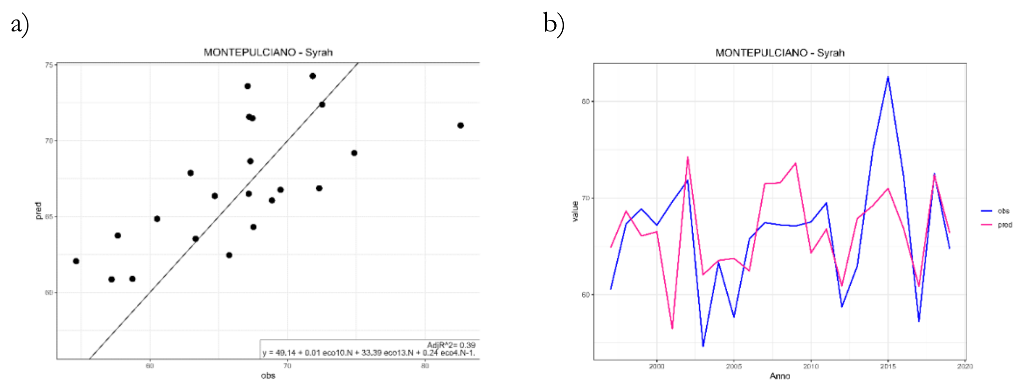


Figure 4.3-11: MON.VN.R - Syrah 1997-2019 panel a) scatter plot of predicted vs observed yield, panel b) time series of predicted (pink) and observed (blue) yield.

In general, for T.FRA.White, the single regression explains a higher portion of yield variability compared to multiple regression. For T.FRA.White using Chardonnay, the index with the highest variance obtained with the single regression is eco3.N-1 (36%), which is also the only index considered by the multi-regressive model. In contrast, for T.FRA.Red, the multiple regression outperforms the single regression approach. (Table 4.3.3). The only significant result for the single regression is a negative correlation with the eco10.N (hydrothermal index during the disease period) for both varieties (Figure 4.3-4). The multi-regressive model accounts for the impact of heat and water stress on yield, selecting as predictors eco6.N, eco11.N, eco12.N, and eco13.N (Figure 4.3-7), increasing the overall representation of the yield variability by 18% (Merlot) and 13% (Cabernet Sauvignon Table 4.3.3). For MON.VN.R, the multi-regressive approach does not improve the single regression significantly. There is a slight improvement observed for Cabernet Sauvignon (1%) and Syrah (3%), while there is a decrease of 2% for Merlot (Table 4.3.3)

Table 4.3.3: This table compares the variance between single and multi-regression approaches. It includes the determination coefficient (Coef.) and p-value (p), along with the period on which the correlations are computed (indicated by the 'Period' column). "Var %" indicates the percentage of yield variance explained by the model. "MaxVar % SR" represents the explained variance associated with the maximum significant single regression (SR), while "Var.diff %" is the difference between "MaxVar % SR" and "Var %" in percentage.

case	Coef.	p	Period	Var %	MaxVar % SR	Var.diff %
T.FRA.WHITE Chardonnay 170 g*L-1	**0.57**	0.05	1997-2009	32%	36%	-4%
T.FRA.RED Merlot	**0.71**	0.01	1997-2010	50%	32%	18%
T.FRA.RED Cabernet Sauvignon	**0.67**	0.01	1997-2010	45%	32%	13%
MON.VN.R Cabernet Sauvignon	**0.53**	0.01	1997-2019	28%	27%	1%
MON.VN.R Merlot	**0.50**	0.01	1997-2019	25%	27%	-2%
MON.VN.R Syrah	**0.55**	0.01	1997-2019	30%	27%	3%

4.5 Conclusion

The impact of climate variability on yield is assessed using ecoclimatic indices and applying single and multiple regression analyses. The advantage of using ecoclimatic indices is the possibility to observe plant stress at specific stages of plant development. Working at the local level, with data collected by consortia, allows a tailor-made analysis for specific varieties and the direct involvement of winegrowers, who can provide information on the specific needs of their region and cultivation.

This study connects ecoclimatic indices to yield through single and multiple regression. However, Shanmuganathan et al. (2010) for New Zealand, proposes a more complex approach that uses data mining techniques. Their assessment also considers grape quality, which is not addressed in this work. The paper addresses some of the issues mentioned by Laurent et al., (2021) regarding yield assessment. Specifically, the agro-model used can account for site-specific phenomena occurring during the yield formation process. Additionally, a multi-regressive model serves as the basis for constructing an eventual composite yield index that can be used for modelling future yields. To achieve this, it is important to strengthen the involvement of wine consortia and stakeholders, as suggested by Naulleau, Gary, Prévot, Berteloot, et al., (2022)

Modelling grapevine yield using climate data is challenging, specifically for wine producing regions in protected appellation areas (European AOP), where yield limitation might be set in the regulation rules of each appellation. Besides, winegrapes are cultivated in a large range of climate conditions (Bois et al., 2016; Puga et al., 2022), where climate constraints on yield differ: drought in semi-arid climates (Bécart et al., 2022; Naulleau, Gary, Prévot, Berteloot, et al., 2022) and frost and diseases in humid wine producing regions (Cradock-Henry & Fountain, 2019; Gustafsson & Mårtensson, 2005; Shaw, 2017). Furthermore, grapevine yield is the result of phases that take place during at least one and a half years, and the consequences of climate during each phase might be either progressive (e.g. grapevine water deficit impact on berry size) or sharp (e.g. damage produced by hail or severe winter cold or spring frost events). Hence the use of linear models combining only up to 3 explanatory variables is probably too simple to establish a fine prediction of yield. However, the use of more complex modelling (polynomial regression, general linear models, or machine learning algorithms such as Random Forest or neural network, etc.) was considered inappropriate because of the small size of the data sample (12 to 22 years) available for each wine producing region.

Although this study was conducted at a local scale using E-OBS data at a resolution of 11.1 km, it is possible that a higher resolution could improve the performance of the phenological and water balance modelling and enhance the representation of environmental conditions. Furthermore, it is recommended to explore the use of climatic data at a convection-permitting scale to investigate if a more accurate representation of the precipitation field can affect the ecoclimatic indices and their correlation with grape yield.

Despite these numerous limitations (coarse resolution climate data and limited yield history), the modelling allowed to explain 25 to 50% of the variance of the yield, depending on the region and product considered, indicating different explanatory ecoclimatic indices according to the type of region and product considered. Literature concerning yield modelling for grapevine products is rare, and this paper identifies a series of ecoclimatic indices, based on current knowledge of the impact of climate on grapevine biological traits, as promising candidates for yield modelling.

The same methodology can be applied to climate model data and calculate the ecoclimatic indices using future climate projections to investigate environmental change and its potential impact on grape yield.

4.6 SUMMARY

This study connects ecoclimatic indices to productivity through single and multiple regression. The agro-model used can account for site-specific phenomena occurring during the yield formation process, and type of cultivar. The modelling explains 25-50% of the productivity variance based on region and product. Different ecoclimatic indices were found to be explanatory depending on the region and product type. The described methodology can be applied to climate model data to calculate ecoclimatic indices, which can help investigate potential environmental changes and their impact on grape yield in the future.

To investigate the effect of climate variability and change on grape productivity, both bioclimatic and ecoclimatic indices are necessary tools. Chapter 3 aims to provide a comprehensive understanding of how to approach the problem. Additionally, the methodology discussed in the first three chapters serves as a basis for the development of climate services, such as the service discussed in the following chapter. Chapter 4 discusses the proposal of a fair price for utilising a particular climate service based on its accuracy. The methodology presented can be generalised and applied in other regions, although the focus is on Portugal due to data availability.

5.AN EFFICIENCY FEE FOR CLIMATE SERVICE - VALUATION OF CLIMATE SERVICES FOR VITICULTURISTS: TACKLING FUNGAL DISEASES

Abstract

Viticulturists developing adaptation strategies to mitigate the impact of climate change, which affects a grapevine's physiology and wine typicity, can benefit from climate services. Climate services translate physically based variables, such as temperature and precipitation, into actionable, decision relevant bioclimatic indicators, such as Spring Rain, Heat Stress Days, and Warm Spell Duration. These bioclimatic indicators enable the mitigation of fungal diseases, specifically downy and powdery mildew, as well as sunburn. Accurate seasonal forecasts of these bioclimatic indicators can help farmers with viticulture, labor, and stock management, as well as improve the yield and value of wine-quality grapes. Seasonal forecasts of these indicators are available on the MED-GOLD project's dashboard. This study determines an annual service fee to access these forecasts on the dashboard. The annual fee accounts for the seasonal forecast accuracy over part of the Douro wine region of Portugal, as well as the potential savings and losses of micro (≤ 1 ha) holding grape growers. The revenue generated from this climate service fee exceeds the cost of dashboard maintenance by nearly 10 times, even with a fee which is less than half of the potential savings of the micro holding farmer.

5.1 INTRODUCTION

5.1.1 Practical Implications

Seasonal forecasts and climate projections have the potential to help farmers anticipate upcoming needs and devise plans for a more resilient, sustainable, and efficient future (Born et al., 2021; Buontempo et al., 2020; Vaughan et al., 2019; Wiréhn, 2024). Traditionally, these forecasts and projections included only essential climate variables, such as temperature and precipitation. The forecasts and projections did not include relevant bioclimatic variables, such as Spring Rain, Heat Stress Days, and Warm Spell Duration, which are needed to make agricultural decisions. This problem was compounded by the fact seasonal forecasts and climate projections are not easily accessible, both in terms of understanding and use for farmers. To tackle these problems, the European Union funded the MED-GOLD project (https://www.med-gold.eu/) through its Horizon 2020 research and innovation programme.

The MED-GOLD project ran from December 2017 until May 2022. As part of the MED-GOLD project, a simple-to-understand and easy-to-use dashboard (https://dashboard.med-gold.eu/) was created. The MED-GOLD Dashboard covers three time periods: the historical climate (1979 - 2020), seasonal climate forecasts (1993 - 2021), and long-term climate projections (2031 - 2060; 2071 - 2100) (Dell'Aquila et al., 2023). The MED-GOLD Dashboard provides essential climate variables, as well as bioclimatic indicators, for three key agricultural sectors of the Mediterranean, namely grapes, olives, and durum wheat. For each sector, an industrial partner was found to co-design, co-develop, test, and assess the added value of the MED-GOLD proof-of- concept agricultural climate service. In the grape sector, the industrial partner was SOGRAPE Vinhos (Dell'Aquila et al., 2023), the largest wine company of Portugal. They manage over 1600 ha of vineyards and produce wines across 5 countries and 3 continents. Fungal diseases and sunburn cause considerable losses in grape yield (20 - 30%) and value (20%) in the single harvest each year (António Graça, 2021). Through the co-development of process with SOGRAPE Vinhos (Chou et al., 2023; Dell'Aquila et al., 2023; Marta Bruno Soares et al., 2019), seasonal forecasts of Spring Rain, Heat Stress Days, and Warm Spell Duration, with a minimum accuracy of 70% compared to observations, were identified as being helpful for explaining incidences of fungal diseases and sunburn, while improving viticulture, labor and stock management for grape growers in the Douro Valley (Northern Portugal). In this work, we have determined an appropriate annual fee to access the seasonal forecast of these three bioclimatic indicators on the MED-GOLD dashboard. To determine the fee, we first calculated the seasonal forecast performance of these three indicators over the Douro Valley wine region. The seasonal forecast performance accounts for the hit-rate, false-alarm rate, and accuracy of the European Centre for Medium Range Weather Forecasts (ECMWF) seasonal forecasts version 5 data (Johnson et al., 2019; Stockdale et al., 2018), known as SEAS5, compared to the ECMWF reanalysis version 5, known as ERA5, of historical weather and climate data (Bell et al., 2021; Hersbach et al., 2020). The second component of determining the annual fee, includes a cost-benefit analysis identifying the potential savings and losses of a micro holding grape grower. Micro holding grape growers make up most grape growers in Douro Valley wine region, making their perspective essential when determining a climate service fee. Combining the results of both analyses, a range of "access fees" was proposed according to the accuracy of the seasonal forecast.

The results showed the SEAS5 seasonal forecasts of the three bioclimatic indicators starting in March to be 54-60% accurate, compared to the ERA5 reanalysis, for hotter- and/or wetter-than-normal conditions over the Douro region. These forecast accuracies are statistically better than assuming the upcoming season will be "normal", although lower than preferred. Nonetheless, this climate service adds value to the traditional agri-food system.

If the seasonal forecast accuracy is 100%, incorporating it into the decision-making process could save farmers more than 10% of annual harvest earnings in an average year and more than 15% in a hotter and/or wetter than normal year. Potential losses due to false alarms, however, must be accounted for. We propose an annual climate service fee of € 20/year to access the seasonal forecasts, over the Douro region, starting in March. This fee was determined by considering: (i) the financial loss due to fungal diseases and sunburn; (ii) the maximum potential savings of a seasonal forecast in terms of labor and fungicide; and (iii) the 50% accuracy of the seasonal forecasts starting in March. In addition, we have shown that the potential revenue that could be generated from the MED-GOLD dashboard seasonal forecast alone, by charging the (minimal) access fee, is almost 10 times the annual maintenance cost of the dashboard. Thus, the revenue could cover adaptive and preventive maintenance activities to improve the MED-GOLD dashboard according to user feedback.

Lastly, the approach developed in this work, to determine the MED- GOLD Dashboard access fee, showed how improvements to the seasonal forecast accuracy directly impact the value of the climate service. The approach we used to identify the value of the climate service tackling fungal disease and sunburn can be applied to other MED-GOLD sector products and climate services. For example, those related to the olive or wheat sectors or future climate projections.

5.1.2 MED-GOLD project

The MED-GOLD project was a proof-of-concept agricultural climate service which focused on three staples of the Mediterranean food system: grapes, olives, and durum wheat. Scientific and industrial experts partnered together to demonstrate the added value of co-designing and co-developing information-driven responses to climate changes. A comprehensive description of the co-development of the MED-GOLD pilot climate service for the grape/wine sector is described in (Dell'Aquila et al., 2023). The agricultural climate service for the wine sector was co-developed with SOGRAPE Vinhos, the largest producing wine company in Portugal. SOGRAPE's participation as a co-designer in this pilot climate service acts as a catalyst, accelerating the engagement within the wine sector. Having a single dedicated "champion user" in the co-production of the climate service tool was particularly important in the Douro wine region (Figure 5.1-1Figure *5.1-1*: The Douro Wine Region in Northern Portugal. Image Credit: SOGRAPE (António Graça, 2021).) due to the distribution of grape growers. From the Douro wine region's holding size distribution, shown in Figure 5.1-2, it can be seen that ≥ 60% of grape growers have micro holdings (≤ 1 ha). With only one grape harvest per year, the income generated by the harvest on a micro holding is merely supplementary income for the grape grower. Often, these grape growers can not commit the time needed for the entire process of climate service co-production, which includes repeated interviews, testing and iterating products/services, etc., in addition to their regular jobs. SOGRAPE has the knowledge, resources, and personnel to dedicate to the co-production process with its own fulltime Research & Development team. They participate in research projects and disseminate results to grape-growers and the wider wine sector; including the ~ 1000 grape growers who sell their products to SOGRAPE in the Douro wine region (António Graça, 2021).

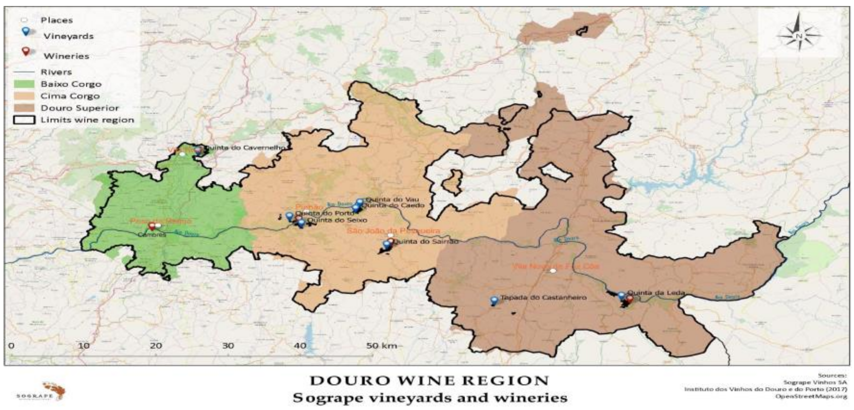


Figure 5.1-1: The Douro Wine Region in Northern Portugal. Image Credit: SOGRAPE (António Graça, 2021).

5.1.2.1 *Douro Wine Region*

The Douro wine region is a mountainous region in Northern Portugal (Figure 5.1-3) with a very steep terrain. Tiered terraces have been etched along its steep slopes. The rocky, schistous soil of the Douro region is dry and poor in nutrients but has excellent heat retaining properties. With terraces offering different variations in altitude, exposures to sun and wind, soil fertility, and atmospheric humidity, the Douro region is a host to a variety of grape types. The six principal red and white grape varieties include, Tinta Amarela, Tinta Barroca, Tinto Cão, Tinta Roriz, Touriga Nacional, Touriga Francesa, Gouveio, Arinto, Malvasia Fina, Rabigato, Viosinho, and Códega.

5.1.2.2 *Fungal Diseases and sunburn*

Some grape varieties, such as Touriga Francesa, which account for approximately 25% of all grapevines in the Douro wine region (Instituto da Vinha e do Vinho, 2021), have tight grape bunches. This makes them more susceptible to fungal diseases, particularly when warm and moist conditions persist and air can not circulate in the grape bunches(António Graça, 2021)

Atmospheric humidity in the Douro wine region, in particular after rain in the spring, can drive risk of infection by Plasmopara viticola (downy mildew) (Figure 5.1-4a) (António Graça, 2021). When downy mildew emerges during critical phenological stages, such as at blossom or at fruit set, grapes are damaged, ultimately reducing yield. Downy mildew can be avoided by the procurement and application of protection products, such as copper-based formulations. Determining when protection products should be applied relies on daily monitoring of temperature, rainfall, and vegetation conditions. For example, the period after budbreak, when daily average temperature exceeds 10 °C and shoots are at least 10 cm long, a rainfall event of 10 mm over 2 days prompts visual inspections for fungal disease development (António Graça, 2021). Fungal development in susceptible areas has, historically, appeared one week after the rain event. After a visual verification of fungal development and protection products have been applied, atmospheric humidity conditions must be monitored as ensuing rainfall events may provoke secondary infections. Should this occur, protection products must be reapplied. Protection products may be applied multiple times throughout the growing season (António Graça, 2021). Downy mildew protection products, however, have expiration dates over which they lose activity. Their short shelf life means any quantity not used during the growing season should not be carried over.

When high atmospheric humidity conditions are combined with mild-warm temperatures, sheltered conditions can be created around the bunch zones, especially in high-vigour grapevines. These unaerated bunches may be infected by Erysiphe necator (powdery mildew) (Figure 5.1-4b) (António Graça, 2021). Should an infection of powdery mildew occur during the veraison stage of grape bunch development, the result is a loss of grapes quality. Powdery mildew can be avoided through manual trimming and leaf thinning by labourers, known as active canopy management. These exposed grape bunches, however, are susceptible to sunburn as a result of direct solar radiation exposure (Figure 5.1-4c) when temperatures exceed 35 °C (António Graça, 2021; Hunter & Bonnardot, 2011). This is particularly problematic during heatwaves. In addition, when temperatures exceed 35 °C, the grapevine undergoes heat stress. The plant closes its stomata and photosynthesis no longer occurs. As the plant uses more water to cool its tissues, it can lead to a disruption in flowering or berry and leaf dehydration, and sunburn. Both sunburn and powdery mildew lead to a decrease in crop quality and value, but active canopy management can prevent the risk of either occurring. With a single harvest per year, the yield and value of an entire production of wine quality grapes can be significantly reduced, or even lost, due to weather phenomena and viticulture mismanagement. In the Douro region, SOGRAPE found downy mildew typically caused a yield loss of 30%, whereas sunburn caused a yield loss of 20%, and powdery mildew caused a value loss of 20%. These values are the same for all holdings, regardless of size (António Graça, 2021).

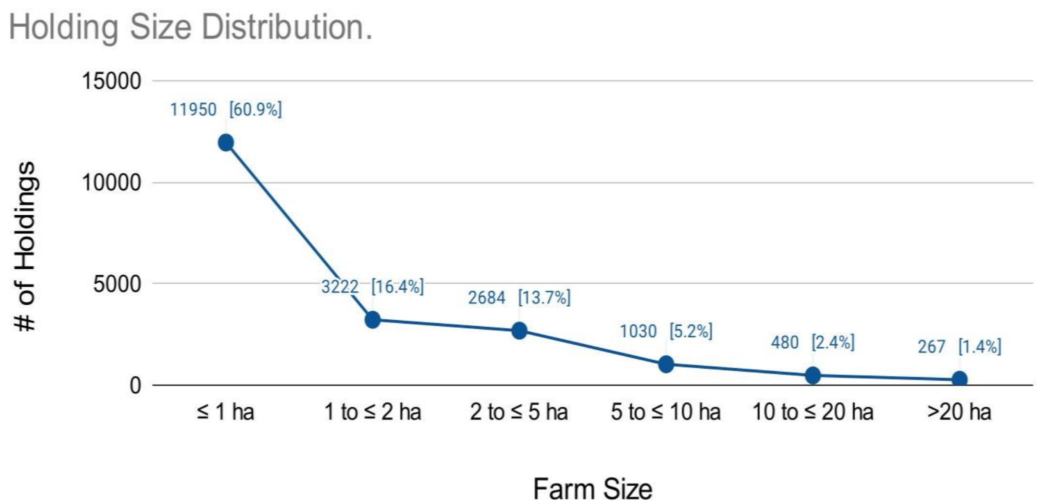


Figure 5.1-2: Distribution of holdings according to Farm Size in the Douro wine region. Percentage of total distribution shown in square brackets. Data Source: Instituto dos Vinhos do Douro do Porto, (2020)**.**

Figure 5.1-3: Mountainous and rocky terrain of the Douro Wine Region. Photo Credit:SOGRAPE (António Graça, 2021)**.**

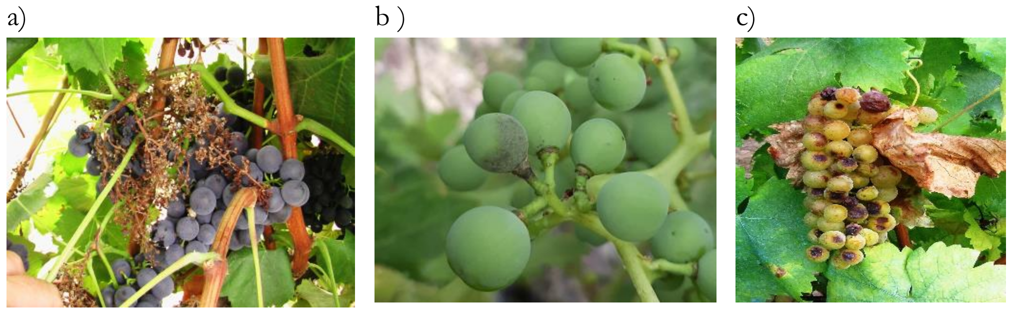


Figure 5.1-4: Examples of (a) Plasmopara viticola, known as Downy Mildew. (b) Erysiphe necator, known as Powdery Mildew and (c) sunburn. Photo Credit: SOGRAPE (António Graça, 2023)

5.1.3 Bioclimatic Indicators

Through several workshops, interviews, and focus group discussions with different levels of management, directors, and executives covering SOGRAPE's decision chain in productive and procurement operations the following bioclimatic indicators were identified as being useful for explaining the incidence of fungal diseases and sunburn in grape bunches (Chou et al., 2023; Dell'Aquila et al., 2023; Marta Bruno Soares et al., 2019; Terrado et al., 2023).

These bioclimatic indicators, for the Northern Hemisphere, are defined as:

1. Spring total precipitation (SprR), the total accumulated rainfall from April 21st to June 21st. This indicator is associated with vigorous under-vines growth which increases atmospheric humidity and restricts airflow, contributing to fungal disease risk (Australian Wine Research Institute, 2016; Dell'Aquila et al., 2023).

2. Heat Stress Days (SU35), the total count of days which the daily maximum temperature exceeded 35°C between 1st April and 31st October (Chou et al., 2023). This indicator is associated with the number of days photosynthesis of the plant is limited. After veraison, it can affect the sugar, polyphenol, and aroma precursor concentrations in berries, thereby affecting grape and wine quality (Chou et al., 2023).

3. Warm Spell Duration Index (WSDI), total count of days which the daily maximum temperature exceeded the 90th percentile for at least 6 consecutive days between 1st April and 31st October (Chou et al., 2023). This indicator is associated with dehydration, flowering disruption, and scalding of berries and leaves (Chou et al., 2023).

5.1.4 Climate Service

The workshops, interviews, and discussions also helped determine that the mitigation of fungal diseases and sunburn in grape bunches impacts several operational areas including viticulture, labour, and stock management (Chou et al., 2023; Dell'Aquila et al., 2023; Marta Bruno Soares et al., 2019; Terrado et al., 2023). These areas can benefit from a climate service that helps forecast fungal infection risk and sunburn. Seasonal forecasts of SprR, SU35, and WSDI, with a minimum accuracy of 70% compared to observations, were presented in a format which was easy to interpret, understand, and use would suit this purpose (Chou et al., 2023; Dell'Aquila et al., 2023; Fontes et al., 2016; Marta Bruno Soares et al., 2019; Terrado et al., 2023).

An effective climate service providing forecasts with longer lead times al- lows viticulture management to improve the timing of vineyard operations such as pruning and canopy management, as well as planning fungal disease treatments. Similarly, labour management benefits from improved identification and anticipation of high-demand labour periods for the application of protective treatments and canopy management. Stock management benefits from a climate service that offers adequate anticipation of seasonal climate trends which allows for the early procurement of downy mildew protection products at a lower cost. Additionally, chemical waste can be reduced when the correct amount of downy mildew protection products are purchased.

A climate service that provides accurate seasonal forecasts allows for the timely procurement of fungicide product and hiring of labour to tackle downy and powdery mildew, as well as sunburn, can reduce losses in grape yield and value. For many viticulturists, a key question is "How much is a climate service worth?"

Previous work regarding the climatic service market or the valuation of climate service benefits for adaptation Vaughan et al., (2019), such as in Vogel et al., (2017) and Cortekar et al., (2020), or in improved water management Delpiazzo et al., (2023), have not addressed the issue of access fees. The approach developed in this work to determine an annual climate service access fee, in particular where the fee is linked to the performance of the forecast, is novel.

5.1.5 Valuation of Climate Service

This work determined an acceptable annual fee to access the seasonal forecasts of SprR, SU35, and WSDI on the MED-GOLD Dashboard (described in Section XX). An annual fee for seasonal forecast accuracies of 50%, 70%, and 90% was calculated at the request of SOGRAPE (António Graça, 2021). The overall forecast accuracy depends on the hit-rate, false-alarm rate, missed forecasts, and correct rejections (described in Section XX). The performance of the seasonal forecast is integral for determining the climate service's "value" because it is directly linked to the hiring of labour, product procurement expenditures, and potential savings for the grape growers.

The existing market for the MED-GOLD Dashboard amongst viticulturists in the Douro wine region is driven by micro holding grape growers. Their profit/loss margins will govern the maximum cost of the climate service. Micro holding grape growers indirectly reflect purchasing power and influence purchasing choices. The cost of the climate service must not exceed the potential loss by fungal infection or sunburn, nor significantly reduce profit margins of the grape grower. To determine a valuation of the MED-GOLD Dashboard, it is essential to understand the potential financial gains and losses of a micro holding grape grower due to fungal disease and sunburn. This will be presented in Section XX. In this work, the valuation of climate service was based on: (i) the performance of the seasonal forecasts of SprR, SU35, and WSDI on the MED-GOLD Dashboard (Dunn et al., 2020; Martins et al., 2021); (ii) the cost of inaction of fungal disease; and (iii) the potential savings due to actionable climate knowledge. The aim was to propose a reasonable fee for a climate service tackling fungal diseases and sunburn.

5.1.5.1 *Technical Considerations & Business Sustainability*

In addition, this work determined if the existing market in the Douro wine region, with the proposed fee, can sustain the minimum annual IT infrastructure cost of about € 12000, which was determined during the MED-GOLD project's prototype development. The MED-GOLD Dashboard and the MED-GOLD ICT (Information and Communication Technologies) platforms it relies upon were designed around a Public Cloud-based infrastructure, namely Amazon Web Services (AWS). The main reason for this fundamental architectural choice resided in one of the defining features of Cloud computing: elasticity. While traditional "on-premises" IT infrastructures usually require large capital expenses in order to acquire, configure, build, and maintain a physical data center, publicly available Cloud platforms allow users to dynamically create, manage, and destroy needed IT resources in an elastic way, only generating operating costs when those resources (e.g.: storage, computing units) are actively used. This way, a Cloud-based application, such as the MED-GOLD Dashboard, can still be viable for small-scale scenarios, and, when designed according to best practices, can easily be scaled up as the need arises. For a more detailed description of the technical considerations about the deployment of the MED-GOLD ICT platform and the Dashboard application, please refer to (Wiréhn, 2024). The expected cost of € 12000 included both the MED-GOLD Dashboard web application's infrastructure itself and the entire data processing pipelines it relies upon: source data fetching from the European Union's Earth Observation Programme Copernicus Climate Change Service (C3S) (https://cds.climate.copernicus.eu/) Climate Data Store (CDS), validation and normalization of scripts, indicators calculations, and storage. It is important to note that this cost should be considered as the bare minimum to sustain the recurring cost of the basic Cloud-based IT infrastructure and wouldn't allow for any enterprise-level maintenance or application-level improvements.

5.2 Materials and Methods

5.2.1 MED-GOLD Dashboard

The MED-GOLD Dashboard is user-focused web-based application designed and created to visualise and disseminate relevant climate information for three Mediterranean agricultural sectors. For a comprehensive review of the MED-GOLD Dashboard for the grape and wine sector, please refer to Dell'Aquila et al. (2023). There is also a MED-GOLD dashboard user guide entitled "Deliverable 3.5 A handy easy-to-use manual for stakeholders Wine practitioners of the climate service tool. PART II: the grape/ wine sector." available at https://www.med-gold.eu/documents-deliverables/.

The MED-GOLD dashboard presents climate information provided by the CDS (Buontempo et al., 2020; C3S, 2023). The CDS provides access to numerous quality checked climate data sets including the ECMWF ERA5 reanalysis of historical weather and climate data (Bell et al., 2021; Hersbach et al., 2020), which we used to verify the ECMWF SEAS5 seasonal forecasts of atmospheric and oceanic conditions (Johnson et al., 2019; Stockdale et al., 2018). SEAS5 consists of a 51-member ensemble initialised every month on the first day of the month and integrated for 7 months (Johnson et al., 2019). SEAS5 has a spatial resolution of 0.25 degrees. On the MED-GOLD Dashboard, the SEAS5 was used to compute SprR, SU35 and WSDI starting at different months (March to June) (Calì Quaglia et al., 2022; Doblas-Reyes et al., 2013; Giuntoli et al., 2022). For a comprehensive description of all CDS products used in the MED-GOLD Dashboard, please refer to the project "Deliverable 7.2 Data Management Plan" available at https://www.med-gold.eu/documents-deliverables/). The MED-GOLD dashboard presents the climate information for each of the three time periods (historical climate, seasonal forecasts, and long-term projections) in their own sections. In each of these sections, the climate information is classified into the following three categories: Climate variables (e.g. precipitation); Bioclimatic indicators (e.g. Spring Rain); and Wine Risk Indicators (e.g. Sanitary and Heat Risk). The dashboard is a visualization focused web-based application that also allows users to browse, view, and download climate data. Relevant parameters can be selected one-by-one according to preferred time range, geographic location, scenario type/forecast starting month, climate indicator, etc. The indicators are available in several different formats and visualizations, allowing for easy, quick, and seamless integration into critical decision-making. Users can access and interact with relevant climate information without any programming knowledge or the need to manage large climate data files. The main functionalities of the dashboard were based on specific needs highlighted by SOGRAPE.

The study considers only one component of the MED-GOLD dashboard namely, seasonal forecasts of three bioclimatic indicators.

5.2.1.1 *MED-GOLD Dashboard: Seasonal forecasts*

The seasonal forecasts of each bioclimatic index on the MED-GOLD Dashboard is presented in terciles. The terciles indicate: above normal, normal, or below normal, where 'normal' is defined as the range between the 33rd and 66th percentile over the 1993 - 2020 period from the bioclimatic index derived from the ECWMF ERA5 reanalysis of global weather and climate (Bell et al., 2021; Hersbach et al., 2020). 'Above-normal' is defined as greater than the 66th per- centile and 'Below-normal' is defined as less than the 33rd percentile (Deliverable3.2, 2018; Deliverable3.3, 2018). The values which lie above the upper tercile or below the lower tercile are commonly considered as anomalies in climate science (Deliverable3.5, 2018; European Centre for Medium-Range Weather Forecasts (ECMWF), 2021). The presentation of the indicators as above/below normal is a result of the dashboard's co-development process, taking into account user feedback, allowing for a more diverse range of users of climate information ranging from beginners to advanced (Dell'Aquila et al., 2023; Marta Bruno Soares et al., 2019).

In this study, we have only considered conditions under which grape growers would benefit from fungicide and sunburn prevention, namely hotter- and/or wetter-than-normal conditions, as recommended by SOGRAPE. As such, we analysed and reported the performance of the three bioclimatic indicators when above-normal conditions were forecasted in SEAS5 compared to ERA5 reanalysis. This study should not be confused with a comprehensive evaluation of the bioclimatic indicator performance seasonal forecast, which would also investigate the causes of deteriorating performances. For an advanced analysis of the seasonal forecasts of the bioclimatic indicators for the wine sector please refer to Chou et al., (2023).

5.2.2 Performance metrics of Bioclimatic Indicators

The performance of SEAS5 seasonal forecasts of above-normal conditions, from 1993 - 2020, for each of the three indicators (SprR, SU35 and WSDI) was calculated for the region over the SOGRAPE company vineyards located in the Douro wine region (lon 7° 0' 59" W , lat 41° 1' 20" N). The SEAS5 resolution of 0.25 degrees translates to approximately 21 km by 21 km over this grid box, which covers approximately 441 km^2. The bioclimatic indicators are homogeneous over the grid-box.

The performance of each of the three indicators is based on the hit-rate, false-alarm-rate, and accuracy of the SEAS5 seasonal forecasts compared to the ERA5 reanalysis (Hogan & Mason, 2011). The definitions of hit-rate, false-alarm-rate, and accuracy used are as follows (Eqn. 1, 2, 3):

$$H = \frac{a}{a+c} \qquad \text{(Eqn. 1)}$$

$$F = \frac{b}{b+d} \qquad \text{(Eqn. 2)}$$

$$A = \frac{a+d}{a+b+d+c} \qquad \text{(Eqn.3)}$$

Where:

- a denotes a Hit. It is the number of times an event was correctly forecasted and occurred.
- b denotes a False-Alarm. It is the number of times an event was fore- casted but did not occur.
- c denotes a Miss. It is the number of times an event occurred but it was not forecasted.
- d denotes a Correct-Rejection. It is the number of times an event was not forecasted and did not occur.

Table 5.2.1: Contingency table.

		Forecasted	
		Yes	No
Observed	Yes	(a) Hit	(b) Miss
	No	(c) False	(d) Reject

The MED-GOLD dashboard provides seasonal forecasts of SprR, SU35 and WSDI starting at different months (March to June) (Brönnimann, 2007; Calì Quaglia et al., 2022; Giuntoli et al., 2022). The earlier an accurate forecast can be made the better is for the climate service users. For each index, and for each starting month, the three performance metrics (hit-rate, false-alarm-rate and accuracy) are calculated. The performance of the bioclimatic indicators over the Douro valley gives a complete picture of the quality product the MED-GOLD project provides the grape growers and helps determine the value of the climate service.

For grape growers using seasonal forecasts for planning purposes, both 'false alarms' and 'missed alarms' are problematic. In the case of a false alarm, the seasonal forecast recommends that grape growers purchase product and hire labour to deal with a hotter- and/or wetter- than-normal summer, an investment that is not needed in the end. The grape growers' money would be lost when a False-alarm occurs. In the case of a missed forecast of a hotter- and/or wetter-than-normal summer, no actionable climate knowledge is gained from the seasonal forecast. The grower does not lose additional money through pre-purchase of unnecessary goods and services on the basis of the forecast suggestion. Their expenses, as well as losses in yield and value, in the season, would be the same as without a climate service.

This work determined the value of the actionable climate knowledge that can be gained from seasonal forecasts by considering the amount of money that could be saved by using the climate service, as well as the impact of missed and false alarms. In other words, we conducted an ecosystem service to find the right value of the climate service.

5.2.3 Ecosystem Services valuation approach

Ecosystem Services (Burkhard et al., 2018) constitute a socio-ecological approach to analyse the relationship among ecosystems, economics, and social systems trying to measure and quantify the economic impact due to ecosystem changes. According to the Common International Classification of Ecosystem Services (CICES v.5.1 Haines-Young and Potschin-Young, 2018) classification, in agricultural fields, ecosystem services related to fungal diseases are included in regulating services: to control, prevent, and reduce the number of fungal disease event.

To find the correct value of a climate service for viticulturists tackling fungal disease and sunburn in the Douro wine region, we took two ecosystem service approaches: 'Market Value' and 'Standard Output'. The approaches are described below. The market value approach is included to provide farmers in the Douro region a relatable analysis, while the standard output approach allows for a generalization of this study to other farmers in the European market.

5.2.3.1 *Market Value*

The Market Value approach took into account the average yield, yield loss, and price of good quality grapes, over a six-year period from 2014 to 2019, from a >20 ha property in the Douro wine region (António Graça, 2021). These values were provided by SOGRAPE and assumed to be representative for the region. The value of € 3136/ha was set as the economic value of ecosystem services based on an average yield of 3200 kg/ha with an average price of € 0.98/kg for a good quality yield of wine grapes (António Graça, 2021). We used these values to estimate cost of inaction against fungal diseases and sunburn by vineyard area.

5.2.3.2 *Standard Output*

In addition to the market value approach, we also present a valuation based on the European Union's standard output. The Standard Output (SO) of an agricultural crop is defined as the average monetary value of the agricultural output at farm-gate price, in €/ha (Eurostat, 2023). The European Standard Output values are released by EuroStat every few years, which represents the 5-year average of an agricultural product (crop or livestock)(Eurostat, 2023). According to Eurostat SO 2013 (Eurostat, 2013) the Standard Output of "Vineyards - Quality Wine" is € 2610/ha for the Norte region of Portugal where the Douro wine region sits. This value was used in the following calculations of inaction. The standard output is used as a classification of agricultural holdings by type of farming and by economic size across Europe (Eurostat, 2023). This value was determined by using the average prices from 2011 to 2015 and applied to the 2016 Farm struc- ture survey data (Eurostat, 2013). The standard output includes sales, redeployment, self-consumption and changes in the stock of products, without the costs of transport and marketing, except for those products for which the price for packaging is also included. The standard output does not include direct payments, Value Added Tax (VAT) or taxes on products (European Commission Regulation 1242/2008, European Commission Regulation 1166/2000).

5.2.4 Farm Personas

The valuation of a climate service which forecasts infections risk, allowing for better hiring practices and the deployment of preventative measures, was performed for 3 personas: the ’Reactive Farmer’, the ’Prepared Farmer’, and the ’Pro-active Farmer’. The ’Reactive Farmer’ makes spontaneous decisions according to present conditions; and is most similar to the ’real world’ grape grower who must react in terms of purchasing fungicide and hiring labour as the situation unfolds. The Reactive Farmer is most susceptible to abrupt increases in costs. The ’Prepared Farmer’ uses industry knowledge and experience to prepare for infections and procures some fungicide products ahead of time at a lower cost. This persona has the ability to absorb some loss if labour or products are not needed. Lastly, the ’Pro-active Farmer’ bases their decision to procure fungicide or hire labour entirely on the seasonal forecast. They assume the seasonal forecast is correct all the time (a.k.a. a 100% accuracy). A cost-benefit evaluation was performed for each of these personas for differing seasonal forecast accuracies of the bioclimatic indicators.

5.3 RESULTS

5.3.1 Performance of the bioclimatic indicators

The performance of the three bioclimatic indicators from SEAS5 seasonal forecasts, starting at different months, was compared to the ERA5 reanalysis over the SOGRAPE company vineyards. The hit-rate, false-alarm-rate, and accuracy of SprR, SU35, and WSDI are presented in Table 5.3.1, Table 5.3.2 and Table 5.3.3 respectively. The metrics in Tables 2, 3, and 4 range from 0 to 100%. A forecast with a hit-rate lower than 33% is equivalent to the climatological average range (i.e. within the "normal" range) and as such does not provide actionable climate knowledge to the grape grower. The higher the hit-rate,the better. In regards to the false-alarm rate, a good forecast will have low values. For the accuracy metric, the higher the value, the better.

Table 5.3.1: Spring Rain (SprR) performance metrics for seasonal forecasts starting at different months. The hit-rate, false-alarm-rate, and accuracy are shown in percentages (%).

	Mar	Apr	May	Jun
Hit-Rate	25	25	38	63
False-alarm Rate	24	33	11	11
Accuracy	60	54	73	81

The hit-rate of seasonal forecasts of SprR starting in March and April are only 25%, however, as the season progressed the performance improved, and the hit-rate of the June forecast rose to 63%. The false-alarm rates also improved as the season progressed, going from a maximum of 33% to 11% in June. The overall accuracy of SprR forecasts for wetter-than-normal springs are all well above 33% and is better than assuming the climatological mean. The accuracy is good in May and June, above 70%, however, the forecast starting April is only 54%.

Table 5.3.2:Number of Heat Stress Days (SU35) performance metrics for seasonal forecasts starting at different months. Values are shown in percentages (%).

	Mar	Apr	May	Jun
Hit-Rate	50	40	30	70
False-alarm Rate	44	31	44	33
Accuracy	54	58	46	68

For SU35 the hit-rate for seasonal forecasts were better in March and June compared to April and May. The June forecast had the best hit-rate with 70%. Comparably, May forecasts only had a hit-rate of 30%. The false-alarm rate in both March and May were above 40%, which is high. The overall forecast accuracies of SU35 for warmer-than-normal conditions, for all starting months, were above 46% and better than assuming the climatological mean. The best performance accuracy was in June with 68%. The hit-rates of seasonal forecasts of WSDI, for all starting months, range from 42% to 58%. The false-alarm rate from March through May are quite high, with the April forecast reaching a peak of 50%. Significant improvements are seen in June (14%). The overall forecast accuracies of WSDI for hotter-than-normal conditions, regardless of starting month are greater than 46% for the Douro region and can be considered better than assuming the climatological mean.

Table 5.3.3: Warm Spell Duration Index (WSDI) performance metrics for seasonal forecasts starting at different months. Values are shown in percentages (%).

	Mar	Apr	May	Jun
Hit-Rate	42	42	58	50
False-alarm Rate	36	50	43	14
Accuracy	54	46	58	69

Of the three bioclimatic indicators, the most accurate was SprR. The accuracy of SU35 and WSDI, overall, were nearly identical. Interestingly, the hit-rates of SU35 and WSDI were better than SprR, however, their false-alarm rates were worse.

For all indicators, the accuracy of the seasonal forecasts for hotter- and/or wetter-than-normal conditions were most accurate when starting in June. The relatively poorer performance in April and May, compared to March and June could be related to seasonal predictability and to large-scale phenomena influencing the local scale meteorology in spring (Brönnimann, 2007; Calì Quaglia et al., 2022; Giuntoli et al., 2022). It should be iterated that this study simply reports the accuracy of the seasonal forecast over the SOGRAPE vineyards for the purpose of determining the value of the climate service. This study is not a verification analysis of the seasonal forecasts in general, nor have we investigated the causes of deteriorating performances of the bioclimatic indicators, as found in April. This has been done in the following works of (Chou et al., 2023; Dell'Aquila et al., 2023; Johnson et al., 2019; Stockdale et al., 2018).

5.3.2 Valuation of Climate Service

As mentioned, the cost of the climate service must not exceed the potential loss by fungal infection or sunburn, nor significantly reduce profit margins of a micro holding grape grower. As such, we first determined the cost of inaction against fungal disease. Secondly, we determined the maximum potential savings the seasonal forecasts knowledge can provide. Thirdly, the total cost of the climate service was calculated, which accounts for forecast errors. Lastly, we calculate whether the proposed climate fee can sustain the MED-GOLD dashboard.

5.3.2.1 *Cost of inaction against Fungal Disease*

In Table 5.3.4 the average yield and income for different holding sizes, based on the market value approach, are presented alongside potential cost of inaction due to fungal disease and sunburn. Additionally, the yield loss, according to Eurostat methodology, in terms of standard output prices of good quality grapes was also calculated (Table 5.3.5). We only considered the value of quality grapes necessary for wine in this study and have not considered lower quality grapes.

Table 5.3.4: Cost of inaction against fungal diseases for various holding sizes in terms of market value. Values rounded to nearest Euro.

	1 ha	**5 ha**	**10 ha**	**160 ha**
Avg. Yield (3200 kg/ha)	3200 kg	160000 kg	32000 kg	512000 kg
Avg. Price for quality yield (0.98 €/kg)	€ 3136	€ 15680	€ 31360	€ 501760
Downy Mildew Loss (30% less yield)	€ 941	€ 4704	€ 9408	€ 150528
Sunburn Loss (20% less yield)	€ 627	€ 3136	€ 6272	€ 100352
Powdery Mildew Loss (20% value loss)	€ 627	€ 3136	€ 6272	€ 100352

Table 5.3.5:Cost of inaction against fungal diseases for various holding sizes in terms of Eurostat Standard Output 2013 (Euro/ha) for the Norte region of Portugal (Eurostat, 2013)**.**

	1 ha	**5 ha**	**10 ha**	**160 ha**
Vineyards - quality wine	€ 2610	€ 13050	€ 26101	€ 417615
Downy Mildew Loss (30% less yield)	€ 783	€ 3915	€ 7830	€ 125284
Sunburn Loss (20% less yield)	€ 522	€ 2610	€ 5220	€ 83523
Powdery Mildew Loss (20% value loss)	€ 522	€ 2610	€ 5220	€ 83523

The potential losses presented for the 1 ha holdings range from € 627 - 941 following the market value approach, and € 522 - 783 following the standard output approach. These potential losses are the upper bound of any climate service fee.

5.3.2.2 *Value of actionable knowledge for Fungal Disease and Sunburn*

The next step in the approach developed to determine the value of a climate service for fungal mitigation was to calculate the potential savings a seasonal forecast could provide in terms of early procurement of fungicide and labor. For this we considered the costs associated with an average year (Table 5.3.6) and a hotter- and/or wetter-than-normal year (Table 5.3.7). The values used in the following section for labor costs, the number of sprays of downy mildew protection product, amount of protection product needed, and costs of protection product, were based on those from a holding in the Douro region averaged over a six-year period (António Graça, 2021). On average 9.4 kg/ha of downy product was used per spray, which cost € 9/kg when procured 6 months ahead of time, or € 16/kg when procured 2 weeks ahead of time (António Graça, 2021). For each hectare of the holding, the Pro-Active Farmer could save an additional € 110 in labor (António Graça, 2021) for an accurate seasonal forecast.

Table 5.3.6: Costs associated with the procurement 4 sprays of downy mildew fungicide, typical of an average year, for a 1 ha holding. Savings related to labour included for Pro-Active farmer. Source: SOGRAPE (António Graça, 2021)

	# Sprays procured 6 months ahead	# Sprays procured 2 weeks ahead	**Total Costs**	Savings relative to Reactive Farmer
Reactive Farmer	0	4	€ 601.60	-
Prepared Farmer	2	2	€ 470.00	€ 131.60
Pro-Active Farmer (Forecast accuracy 100%)	4	0	€ 388.40	€ 373.20

Table 5.3.7: Costs associated with the procurement of 6 sprays of downy mildew fungicide, typical of a 'wet' year, for a 1 ha holding. Savings related to labour included for Pro-Active farmer. Source: SOGRAPE (António Graça, 2021)**.**

	# Sprays procured 6 months ahead	# Sprays procured 2 weeks ahead	**Total Costs**	Savings relative to Reactive Farmer
Reactive Farmer	0	6	€ 902.40	-
Prepared Farmer	2	4	€ 770.80	€ 131.60
Pro-Active Farmer (Forecast accuracy 100%)	6	0	€ 507.60	€ 504.80

In the cost-benefit analysis presented in Table 5.3.6 and Table 5.3.7, we assume the Reactive Farmer has to procure all downy mildew protection product 2 weeks ahead of time at a higher cost. The Prepared Farmer has purchased the quantity need for 2 sprays 6 months in advance at a lower price. They must make any additional purchases of protection product needed in the season at a higher price. The Pro-active Farmer assumes the seasonal forecast has a 100% accuracy and purchases all protection product 6 months in advance. The savings relative to the Reactive Farmer is presented for both the Prepared and Pro-Active Farmer.

The results in Table 5.3.6 show that a Pro-Active farmer can benefit from a climate service on an 'average' year relative to both the Reactive and Prepared Farmers. For a seasonal forecast with an accuracy of 100% the Pro-Active farmer could save € 373.20, compared to the Reactive farmer, which is more than 10% of the market value and standard output earned for quality wine grapes on 1 ha. The Pro-Active farmer saves >2.8 times the amount the Prepared farmer saves. Table 5.3.7 shows that the Pro-Active farmer aims to gain much more in wet years, through early procurement, if the seasonal forecast is correct. These values show that the Pro-Active farmer could save 16% of the market value and 19% of the standard output on a 1 ha farm compared to the Reactive farmer. The Pro-Active farmer saves >3.8 times more than the Prepared farmer saves.

In addition, we computed the savings for a various combination of prepared and spontaneous downy mildew sprayings (not shown) to determine range of loss/savings due to early procurement of downy mildew products and labor. For 1 ha, assuming 100% seasonal forecast accuracy, a Pro-active Farmer could save € 175 (for 1 spray and labor) to € 768 (for 10 sprays and labor) compared to Reactive Farmer in downy mildew product costs. In 2016, 10 sprays were needed; it was the maximum number of sprays recorded by SOGRAPE (António Graça, 2021).

While the savings potential from seasonal forecasts are very attractive, the purpose of **Table 5.3.8** is to demonstrate the impact of a missed forecast of a hotter- and/or wetter-than-normal year and similarly a false-alarm forecast. When a forecast is missed, the Pro-Active Farmer still saves money relative to the Reactive Farmer. A 'false-alarm' forecasts of a 'wet' year, however, can lead to a loss for the Pro-Active Farmer through wasted protection product and additional labor. The False-alarm rate of seasonal forecasts must be accounted for in the price of the climate service.

Table 5.3.8: Costs associated with false-alarm and missed forecasts for labour costs and the procurement of 6 sprays of downy mildew fungicide, typical of a 'wet' year, for a 1 ha holding. Source: SOGRAPE (António Graça, 2021)

	# Sprays Procured 6 months ahead	# Sprays to be procured or lost	**Total Costs**	Savings relative to Reactive Farmer
Pro-Active Farmer (Forecast 50% miss)	3	3	€ 705.00	€ 197.40
Pro-Active Farmer (Forecast 50% false)	6	-3	€ 507.60	€ -166.40

5.3.2.3 *Proposed Climate Service Fee*

In Table *5.3.9* the range of potential savings associated with 1 to 10 sprays are presented for the Pro-Active Farmer compared to the Reactive and Pre-pared Farmer. This is assuming a seasonal forecast with a 100% accuracy. Additionally, the average potential savings for 3 to 6 sprays is presented, which is more realistic. This 'averaged potential savings' is what the grape growers aim to gain by using the seasonal forecast of the bioclimatic indica- tors on the MED-GOLD Dashboard. We used this value to help determine a first estimate of an annual climate service access fee, which we took to be 10% of the average potential savings for a seasonal forecast with a 100% ac- curacy. The choice of 10% is a very conservative estimate to give us a lower bound of an annual fee. For simplicity, this initial dashboard access fee is scaled linearly by 50%, 70%, and 90% to represent forecast accuracy. This linear relationship can be adjusted if future studies collect and analyze data from more farmers regarding past financial losses due to fungal infection, as well as the financial changes that occur when some farmers incorporate seasonal forecasts into their decision-making process.

Table 5.3.9: Range of potential savings of the Pro-Active Farmer, compared to the Reactive and Prepared Farmers, for a hotter- and/or wetter-than-normal year, for a 1 ha holding.

				Proposed Fee		
	Savings Range 1 to 10 Sprays	Avg. Savings 3 to 6 Sprays	10% of Avg. Savings	90% accuracy	70% accuracy	50% accuracy
Pro-Active Farmer vs. Reactive Farmer	€ 175 - 768	€ 406	€ 40	**€ 36**	**€ 28**	**€ 20**
Pro-Active Farmer vs. Prepared Farmer	€ 194 - 636	€ 275	€ 28	**€ 24**	**€ 19**	**€ 15**

If using the seasonal forecasts for hotter- and/or wetter-than-normal conditions starting in March, where the accuracy is closer to 50% rather than 100% (see Section 5.3.1), we propose a Climate Service Fee of € 20/year. This minimal fee should not act as a barrier for the adoption of the MED- GOLD Dashboard climate service for protection against fungal disease by viticulturists. While the seasonal forecast accuracy for hotter- and/or wetter-than-normal conditions is best in June, in the context of anticipating hiring labor and the early procurement of fungicides to reduce infection risk, June is too late.

5.3.2.4 *Maintenance and Sustainability of Climate Service for Viticulture*

With a proposed Climate Service Fee of approximately € 20 per year, which is a low estimate, we determined whether the potential market could sustain the maintenance and sustainability of the MED-GOLD Dashboard. Assuming a market uptake of the Douro holding distributions (Fig. 2, for both 30% (conservative) and 50% (realistic, as estimated by SOGRAPE (António Graça, 2021)), we show that an annual income of € 117789 and € 196330 can be generated (Table 5.3.10).

Table 5.3.10: Annual income generated based on 30% and 50% market uptake of Douro holding distributions (Fig. 2) multiplied by an annual climate service fee of € 20.

	Market Uptake of Holding Distributions	
Farm Size	30% Market uptake	50% Market Uptake
≤ 1 ha	€ 71700	€ 119500
>1 to ≤ 2 ha	€ 19332	€ 32220
>2 to ≤ 5 ha	€ 16104	€ 26840
>5 to ≤ 10 ha	€ 6180	€ 10300
>10 to ≤ 20 ha	€ 2880	€ 4800
> 20 ha	€ 1602	€ 2670
Total Annual Income	€ 117798	€ 196330

The calculated annual income far exceeds the expected € 12000/year needed to maintain the MED-GOLD dashboard and accounts for the increased number of dashboard users. This income could cover the costs of continuous monitoring and maintenance of the dashboard's infrastructure; including corrective maintenance (i.e.: technical tasks, including but not limited to correction to an application's source code needed to repair and correct logical and technical defects discovered after the original deployment).

Moreover, the additional income could also be used, through adaptive and preventive maintenance activities, to keep improving the Dashboard according to users' feedback, e.g. by leveraging all eventual new CDS products and databases, increasing climate data resolution, developing, and implementing new relevant indicators, etc.

5.4 Conclusions

The MED-GOLD Horizon 2020 project aimed to demonstrate the added value of climate services for traditional agri-food Mediterranean systems. For the Wine sector, one of the most relevant questions raised in the project was: Where can climate services add value to the decision-making process of wine companies and farmers when climate information is conveniently tailored and presented in a user-friendly manner? One of the main outcomes of the project was the MED-GOLD dashboard which provides essential climate variables, as well as bioclimatic indicators, in a simple-to-understand and easy-to-use manner.

The three bioclimatic indicators, SprR, SU35, and WSDI, analyzed in this study have been co-developed to provide actionable climate knowledge to help mitigate fungal diseases: allowing for early procurement of fungicide products and the hiring of labor for canopy management.

In this climate service-oriented paper, we developed an approach to determine an acceptable annual fee for a micro holding grape growers to access the seasonal forecasts of the three bioclimatic indicators on the MED-GOLD dashboard. To determine the fee, first, we calculated the seasonal forecast hit-rate, false-alarm rate, and accuracy of these three indicators over the Douro Valley wine region. Second, we performed a cost-benefit analysis identifying the potential savings and losses of a micro holding grape grower. The results showed SEAS5 seasonal forecasts of the three bioclimatic indicators, for hotter- and/or wetter-than-normal conditions, starting in March have an accuracy of 54-60% compared to the ERA5 reanalysis over the Douro region. These forecast accuracies were better than assuming the upcoming season will be similar to the climatic average (a.k.a. "normal"). As such, we can see that this climate service adds value to the traditional agri-food system. Micro holding farmers over can benefit from the actionable climate knowledge as a result of the SEAS5 accuracy. Of the three indicators, despite having a lower hit-rate, the overall seasonal forecasts of SprR performed better than SU35 and WSDI because it had lower false-alarm rates. The most accurate forecasts are those starting in June, however, correct as they may be, they bring little value to procure better pricing in products or labor.

The results of the cost-benefit analysis showed that the cost of inaction due to fungal diseases and sunburn ranges from € 627-941/ha using the Market Value approach and € 522-783/ha using the European Commission Standard Output approach. When the seasonal forecasts of the bioclimatic indicators are included in the decision-making process, they can save a farmer more than 10% of the annual income from a harvest for an average year. Similarly, more than 15% of the annual income from a harvest can be saved in a hotter- and/or wetter-than-normal year. These values represent what could be saved when the seasonal forecast accuracy is 100%, however, potential losses due to false-alarms (24%-44% in March) must be accounted for. After taking into consideration the financial loss due to fungal diseases and sunburn (Sec. 5.3.2.1), the maximum potential savings of a seasonal fore- cast in terms of early procurement of labor and fungicide (Sec. 5.3.2.2), and the accuracy of the seasonal forecast starting in March (Sec. 5.3.1) over the Douro region, which is closer to 50% rather than 100%, we propose a Climate Service Fee of € 20/year.

Based on this analysis, a climate service that correctly forecasts the infections risk:

- 90% of the time should cost € 24 - 36.
- 70% of the time should cost € 19 - 28.
- 50% of the time should cost € 15 - 20.

The approach used to determine the proposed climate service fee can be adjusted as performance of the seasonal forecast improves, in terms of hit-rate, false-alarm rates, and overall accuracy. As the seasonal forecast accuracy improves, so does its value to grape growers. The value to grape growers can increase with further developments or iterations of the MED- GOLD Dashboard. Best practices for climate service may include providing performance metrics (such as hit-rate, false-alarm rate, and accuracy) along- side their products in a transparent manner to instill a user's confidence.

The methodology presented in this paper can be extended to the valuation of other MED-GOLD Dashboard indicators (e.g. sanitary risk), regions (e.g. Italy), and time periods (e.g. climate projections). Elements of the methodology which can be generalized for the purpose of determining a user fee include: (i) evaluating the performance of a prediction; (ii) evaluating the financial impact and potential savings of a decision based on different forecast accuracies; (iii) linking the fee to the performance of the service; and (iv) transparent discussions regarding costs from the perspective of both the application user and software developer regarding maintenance. As such, a similar valuation can be performed for other MED-GOLD products created for the Olive and Durum Wheat industries. The annual income generated by the access fee for the seasonal forecast described in this paper would be only one contribution to the total income generated to maintain the MED-GOLD Dashboard.

Lastly, given the proposed fee, the distribution of holdings, and assumed Market Uptake of farmers of the Douro wine region, we showed the annual income generated can easily cover the maintenance of the MED-GOLD Dash- board. This allows surplus revenue to be used for improving the Dashboard according to users' feedback, as well as developing and implementing new relevant indicators, and leveraging new CDS products and databases.

5.5 SUMMARY

In this chapter an economic assessment of a climate service for wine production is presented. This section aims to establish an annual fee for micro holding grape growers to access the seasonal forecasts on the MED-GOLD dashboard. The fee is determined by evaluating the hit-rate, false-alarm rate, and accuracy of the bioclimatic indicators in the Douro Valley wine region. Additionally, a cost-benefit analysis is conducted to assess potential savings and losses for grape growers. It is estimated that the early procurement of labor and fungicide through a seasonal forecast could result in significant savings, considering the financial losses caused by fungal diseases and sunburn. The accuracy of the seasonal forecast for the Douro region starting in March is approximately 50%. A proposed fee of €20 per year is required to access this Climate Service.

This chapter uses a different set of bioclimatic indices compared to the previous chapters and does not focus on Italy. It was part of an international collaboration with MED-GOLD experts. The geographic area was chosen based on the availability of data in the dashboard. The bioclimatic indices used for the assessment were carefully selected for tackling the specific problems of fungal disease and sunburn, after numerous consultations with the users involved in the codeveloping process of the project, namely Sogrape company.

Despite this difference, Chapter 4 adds completeness to the entire work. Its purpose is to link the scientific and theoretical aspects presented in the previous chapters with a practical application, including an economic evaluation. Although it is still a case study, it has the potential to be generalised and applied in other cases.

6.FINAL CONCLUSION

The climate influence on the variability of wine grape productivity in Italy is studied using bioclimatic and ecoclimatic indices at different spatial scales. In addition, a practical application of bioclimatic indices is presented in a case study proposing a fee for a climate service already implemented in the wine sector. At regional scale, the single regression analysis between bioclimatic indices and wine grape productivity shows predominantly positive correlations between productivity and temperature-based indices, suggesting that vineyard management has adapted to the rising temperatures over time. The application of a multi-regressive model based on the optimal combination of the bioclimatic indices is found to be a powerful tool for predicting Italian wine grape productivity across most regions since it accounts for the interplay between temperature and precipitation-based indices. In Trentino Alto Adige, the model explains up to 54% of the variability in productivity at the interannual timescale, and up to 52% in Veneto and Puglia for the long-term variability. Furthermore, the use of multi-regression results in significant improvements in the explained variance, even when none of the bioclimatic indices alone shows significant correlations with productivity (e.g., in Trentino Alto Adige the increase is 39 % for the total variability, and 44 % in Molise at the interannual time scale). In general, the analysis shows that long-term trends in the bioclimatic indices have greater impact on productivity than the interannual climate variability.

Working at a regional scale provides an overview of the entire national territory, but the fragmented nature of the Italian wine sector cannot be framed at this scale. To address this limitation, an extended set of bioclimatic indices is computed at the local scale and linked with productivity data provided by two wine consortia: 'Consorzio per la tutela del Franciacorta' (FRA) in Lombardia and 'Consorzio del vino Nobile di Montepulciano' (MON) in Toscana. At a local scale, bioclimatic indices are found to be effective in explaining the total variability of wine grape productivity, especially in MON, where they do not show significant results at a regional scale. Furthermore, single regressions show statistically significant results only for a limited number of bioclimatic indices, whereas the multi-regression method consistently improves the explained variability and offers potentially usable information in both consortia. In FRA, the multi-regression approach can explain up to 64% of the total variability, which is 29% higher than the single regression approach. Similarly, in MON, the multi-regression approach can explain up to 45% of the total variability, which is 11% higher than the single regression approach. The remaining unexplained variance may depend on other factors than climate, which range from viticultural practices to quality of the data collected. A complete picture of all the factors contributing to the total variability require additional investigation and falls out of the scope of this work. The use of CPM has a limited impact on the results in this study, as temperature primarily influences grape production. However, CPMs may be more useful when precipitation is the key factor. The assessment here provided can be used as a foundation for incorporating CPMs in upcoming impact studies, showing the application of bioclimatic indices in conjunction with grape productivity.

Climate warming is predicted to change the timing of the plants life cycle, which could limit the use of bioclimatic indices calculated on a fixed calendar date, despite the optimal results obtained for the historical period. In fact, under climate change the same calendar date might refer to a different phenological period for the plants. Therefore, an alternative approach based on ecoclimatic indices is proposed. The impact of ecoclimatic indices on productivity in FRA and MON is investigated using both single and multiple regression approaches performing a variety-specific analysis. The results align with the analysis based on bioclimatic indices, in particular confirming that the multi-regression increases the portion of total productivity variability explained. Contrary to expectations, precipitation appears to have a positive effect on productivity in MON, while a limited impact is observed in FRA. This counter-intuitive result is consistent with the results obtained using the bioclimatic indices, suggesting that this may be a characteristic of the MON area or the prevalence of other non-climatic factors influencing productivity.

The various techniques presented can form the basis for building a climate service for the wine sector, such as the one presented in the last chapter, which uses three specific bioclimatic indices (SprR, SU35 and WSDI) for sunburn and fungus disease prevention in grapes. In this case a methodology to calculate an efficiency-related fee, based both on the performance of the seasonal forecast of the bioclimatic indices and the user's decision process is developed. After analysing different decision scenarios linked to the forecast accuracy, a fee of € 20 per year is suggested. This price would generate revenue for the climate service that exceeds the cost of maintaining the MED-GOLD dashboard by almost ten times while providing a useful product for the farmers. Any surplus revenue can be used to improve the dashboard based on user feedback, develop, and implement new relevant indicators, and create new products and databases.

The study acknowledges limitations due to the heterogeneity of the wine sector and productivity data. To address this issue, the study was conducted at both regional and local scales using different climate data and indices. However, it is important to note that grape production for the wine sector is a complex matter and productivity is influenced by various factors besides climate. Therefore, when investigating productivity variability, it is crucial to consider that only a portion of it can be explained by climate variability. Furthermore, when evaluating the performance of a climate service, it is important to consider the limitations mentioned above and the complexity of the system. Additionally, it is crucial to tailor the assessment to the specific purpose of the service. To fully utilize the service, clear and concise information must be provided to the user.

The presented research indicates windows of opportunities for effective climate services linking bioclimatic or ecoclimatic indices directly to productivity and providing more straightforward answers to winegrowers. Such a service would be a valuable tool for estimating changes in productivity at the seasonal, decadal and multidecadal time scales, by integrating climate information from seasonal forecasts, decadal predictions, and future climate projections, respectively. These results also emphasise the importance of local-scale investigation and user involvement in the conception and tailoring of climate services.

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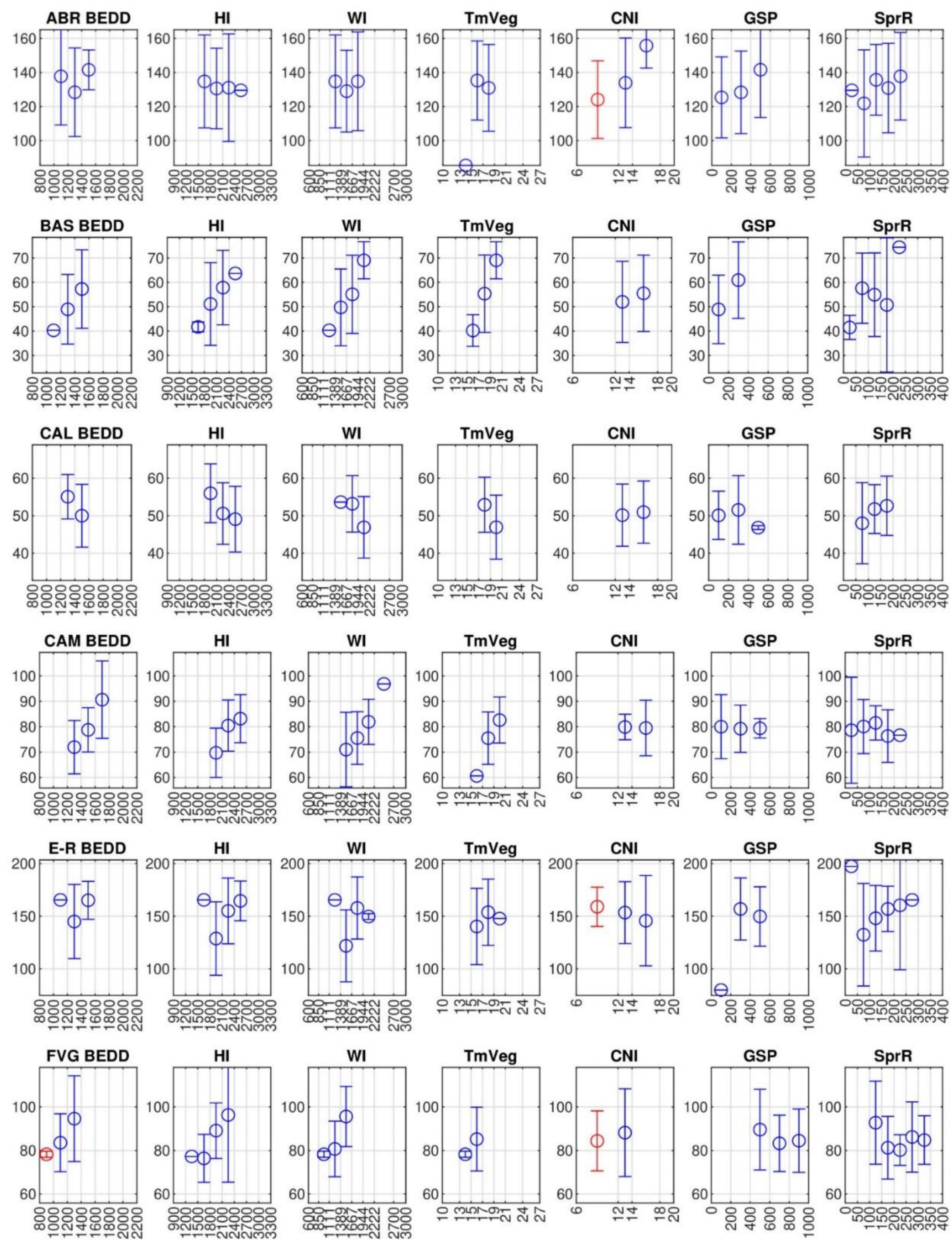
APPENDIX A. ASSESSMENT OF CLIMATE IMPACT ON GRAPE PRODUCTIVITY: A NEW APPLICATION FOR BIOCLIMATIC INDICES IN ITALY

Massano, L., Fosser, G., Gaetani, M., & Bois, B. (2023). Assessment of climate impact on grape productivity: A new application for bioclimatic indices in Italy. Science of the Total Environment, 905. https://doi.org/10.1016/j.scitotenv.2023.167134

Table A 1 Mann Kendal Z and Sen's Slope of the trend analysis of vineyard area, production, and productivity. The * and bold font marks statistically significative trend (p<=0.05)

	Area		Production	
Cod.Reg	Z	Sen's Slope [ha/year]	Z	Sen's Slope [10^3 q/year]
ABR	-0.5	-18.87	0.88	9.71
BAS	-7.05	**-426.79***	-4.13	-16.11*
CAL	-6.95	**-716.71***	-6.48	-38.19*
CAM	-7.75	**-750.86***	-6.93	-57.29*
E-R	-7.98	**-661.60***	-3.41	**-90.69***
FVG	-0.24	-8.86	1.93	7.45
LAZ	-7.87	**-1.51 10^3 ***	-7.07	**-178.41***
LIG	-7.17	**-165.96***	-6.11	**-12.04***
LOM	-6.86	**-283.52***	-4.83	**-26.27***
MAR	-7.7	**-537.54***	-6.21	**-70.33***
MOL	-6.89	**-117.80***	-4.14	**-7.87***
PIE	-8.08	**-861.62***	-6.16	**-59.66***
PUG	-7.38	**-1.61 10^3 ***	-2.16	**-72.74***
SAR	-7.95	**-1.22 10^3 ***	-5.2	**-54.07***
SIC	-7.56	**-2.16 10^3 ***	-5.87	**-244.63***
TOS	-7.92	**-1.04 10^3 ***	-5.37	**-59.22***
TRA	1.3	15.29	-0.4	-1.52
UMB	-6.96	**-330.83***	-4.94	**-18.10***
VDA	-7.6	**-15.47***	-6.29	**-1.16***

	Area		Production	
Cod.Reg	Z	Sen's Slope [ha/year]	Z	Sen's Slope [10^3 q/year]
VEN	-3.89	-566.17	-0.68	-16.53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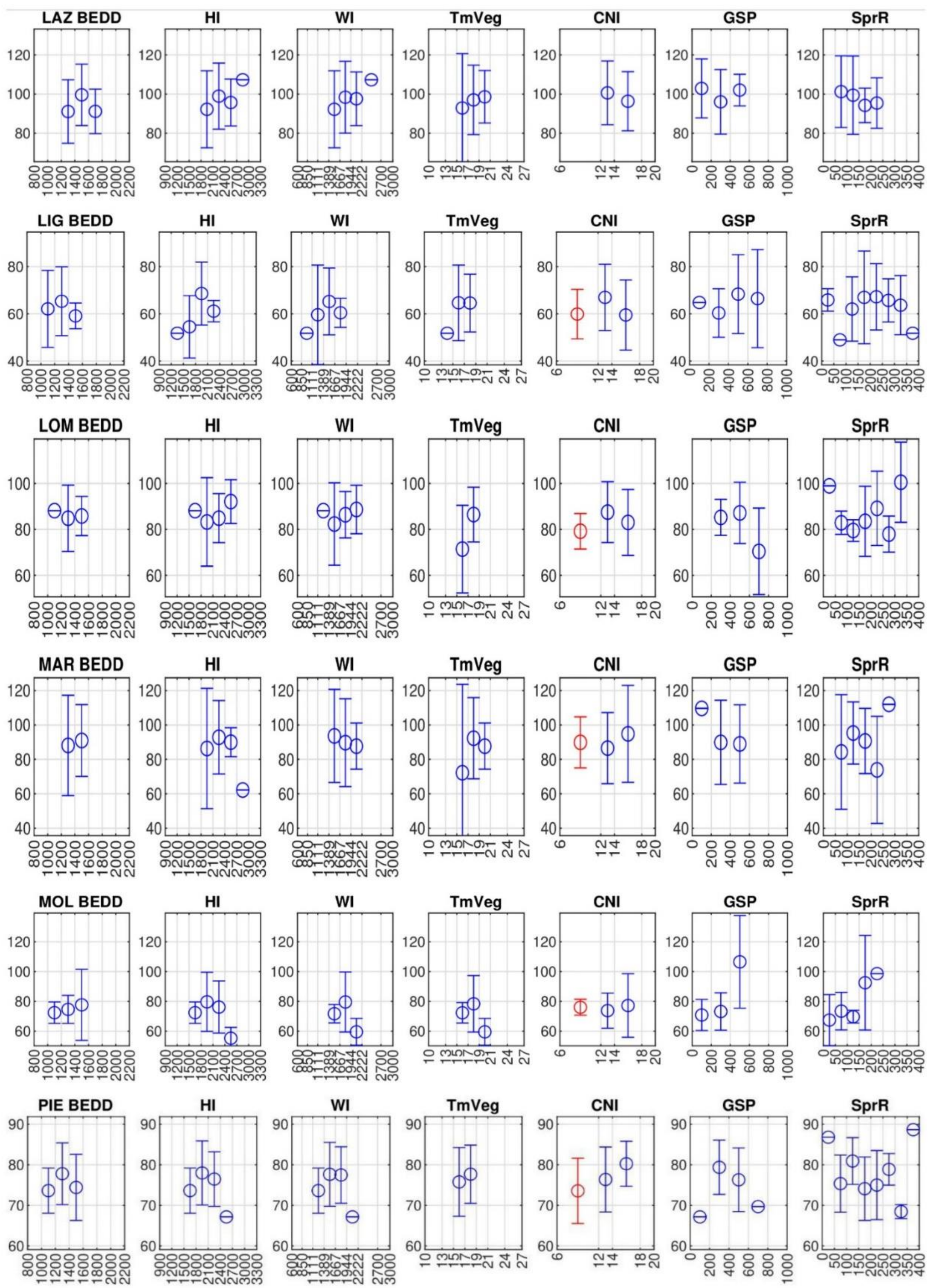
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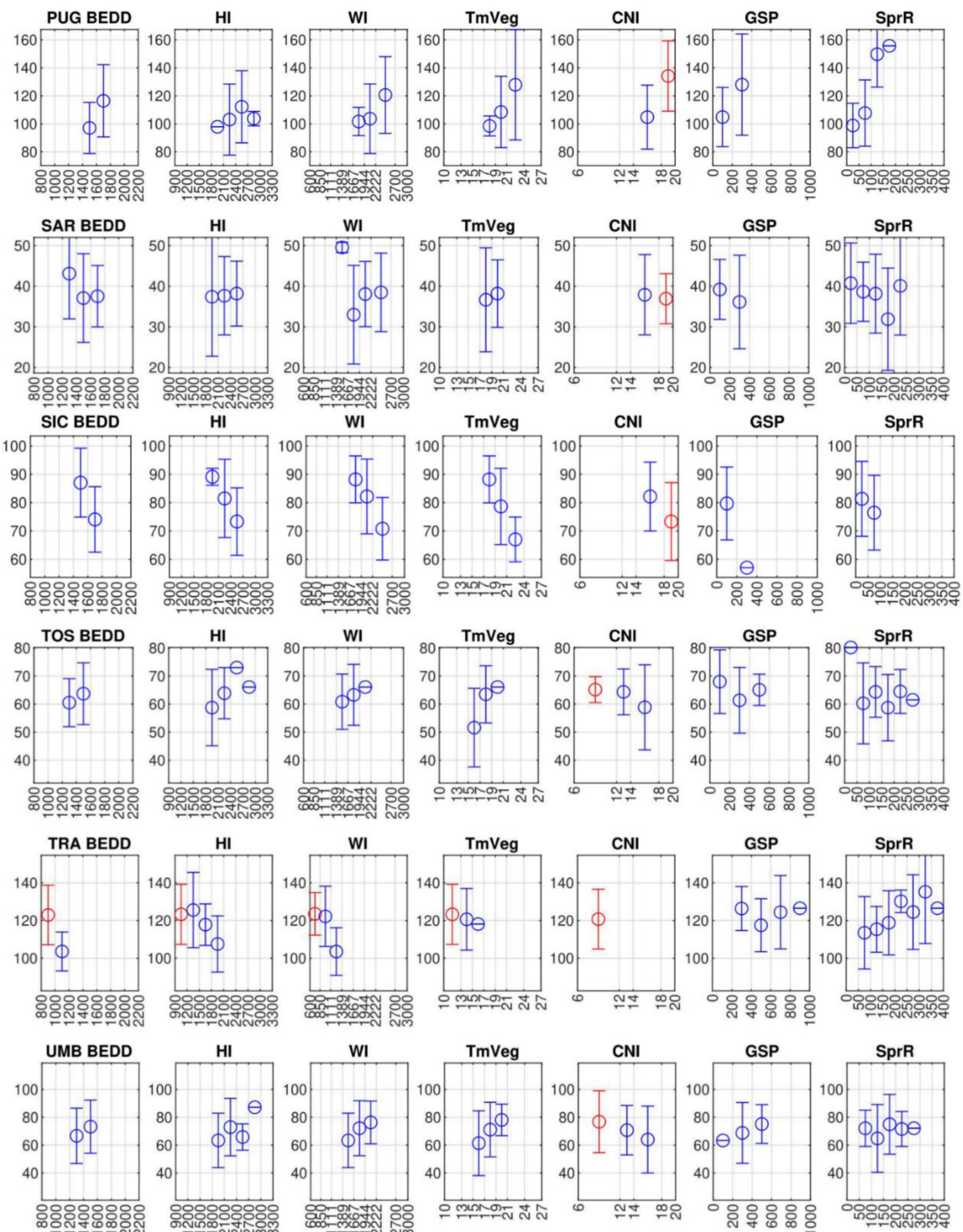
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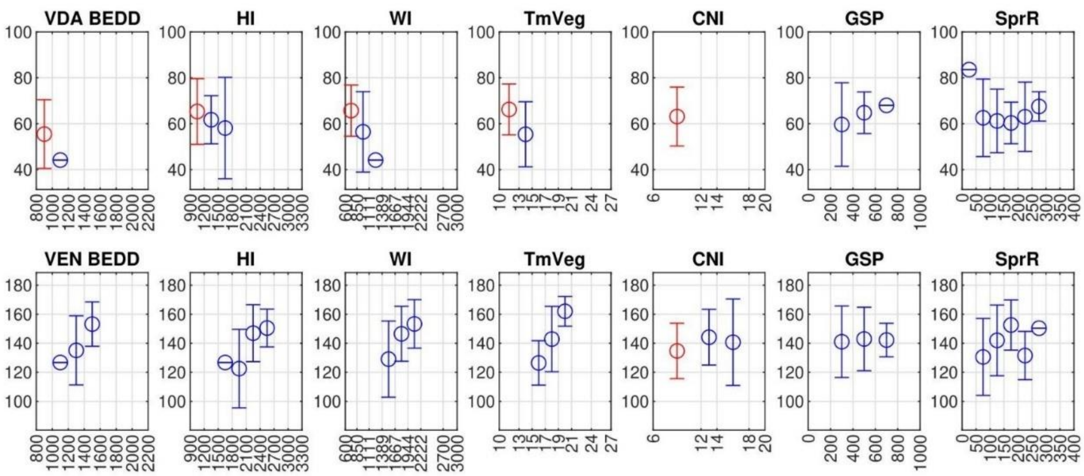

Figure A 1: Characterisation of grape productivity by classes of bioclimatic indices. Circles represent the mean productivity within each class, vertical bars represent the standard deviation. In red, productivity values associated with classes not favourable to grape growing.

Table A 2: Multi regression coefficient raw data

Cod.Reg	(Intercept)	TMVEG	WI	BEDD	HI	SprR	CNI	GSP
ABR	85.24	2.71	-	-	-	-	-	-
BAS	-26.13	-	0.05	-	-	-	-	-
CAL	112.32	-	-	0.04	-0.05	-0.08	-	-
CAM	-603.68	68.73	-0.32	-	-	-	-	-
E-R	-1 488.34	156.87	-0.69	-	-	0.16	-	-
FVG	108.61	-	-	-0.20	0.12	-0.04	-	-
LAZ	136.51	-	-	-	-	-0.07	-1.94	-
LIG	30.74	-	0.08	-0.11	0.03	-	-	0.02
LOM	67.01	-	-	-	0.01	0.12	-	-0.08
MAR	72.61	-	-	-	0.01	-	-	-
MOL	94.12	-	0.23	-	-0.20	-	-	-
PIE	63.75	-	-	-	-	-	1.68	-0.02
PUG	131.60	-	0.25	-	-0.22	-	-	-0.07
SAR	47.21	-	-	-	-	-	-	-0.05
SIC	258.27	-8.53	-	-	-	-0.14	-	-
TOS	60.57	-	-	-	-	0.02	-	-
TRA	380.84	-32.44	-	0.15	0.06	0.19	-	-0.12
UMB	-75.32	8.10	-	-	-	-	-	-
VDA	117.03	-4.26	-	-	-	-	-	-
VEN	-68.59	-	-	-	0.08	0.15	-	-

Table A 3: Multi regression coefficient interannual time scale.

Cod.Reg	(Intercept)	TMVEG	WI	BEDD	HI	SprR	CNI	GSP
ABR	0.12	3.12	-	-	-	-	-	-
BAS	0.25	-	-	-	-	-0.11	-	-
CAL	-0.23	-	-	-	-0.03	-0.08	-	-
CAM	0.30	54.54	-0.16	-0.09	-0.06	-0.04	-	-
E-R	0.02	122.02	-0.81	0.18	0.18	0.27	-	-
FVG	-0.18	-22.14	-	-	0.09	-	-	-
LAZ	0.00	86.23	-0.38	-	-	-	-	-
LIG	1.14	-	0.08	-0.12	0.04	-	-1.83	-
LOM	-0.03	-	-	-	-	0.06	-	-
MAR	0.36	-	-	-	0.02	-	-	-
MOL	3.39	-	0.40	-0.18	-0.32	-0.17	-	-
PIE	0.01	-	-	-	-	-	1.93	-0.02
PUG	0.24	-	-	-	-	-0.13	-	-
SAR	-0.07	-	-	-	-	-	-	-0.05
SIC	0.05	-5.25	-	-	-	-0.14	-	-
TOS	-0.05	-	-	-	-	-	-	0.02
TRA	1.32	-14.95	-	-	0.12	0.19	-	-0.13
UMB	0.61	53.48	-0.23	-	-	-	-4.36	-
VDA	-0.19	-	-	-	-	0.04	-	-
VEN	0.65	-	-	-	0.09	0.15	-	-

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Assessment of climate impact on grape productivity: A new application for bioclimatic indices in Italy

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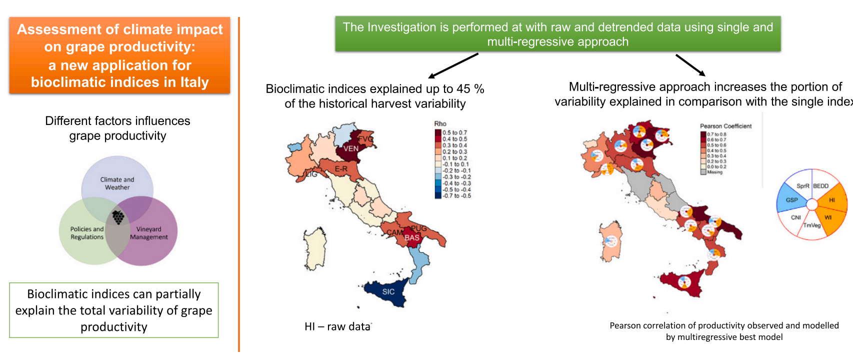
HIGHLIGHTS

- Viticulture in Italy is facing additional challenges due to changing climate.
- Bioclimatic indices are used in conjunction of grape production data in Italy at regional level.
- Individual bioclimatic indices partially explain variability in grape productivity.
- A multi-regressive approach increases the variability explained by individual indices.

GRAPHICAL ABSTRACT



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ABSTRACT

Italy is a world leader for viticulture and wine business with an export valued 7 billion of euros in 2021, and wine being the second most exported product within the national agri-food sector. However, these figures might be threatened by climate change and winegrowers call for more reliable local information on future impacts of climate change on viticulture.

The study aims to understand the impact of climate on wine production in Italy using grape productivity data and bioclimatic indices. Using temperature and precipitation observations from the E-OBS gridded dataset, a set of bioclimatic indices recommended by the International Organisation of Vine and Wine guidelines is calculated and correlated with grape productivity data at the regional scale (Nomenclature of territorial units for statistics, NUTS, level 2) over the last 39 years (1980-2019). The study investigates how both long-term change and natural variability of the bioclimatic indices impacted on grape productivity. Both single and multi-regression approaches are applied to assess the portion of grape productivity variability explained by the selected indices.

When the single-regression approach is applied, the correlations between bioclimatic indices and grape productivity explain up to the 45 % of total production variability, however they are statistically significant only in few regions. Conversely, the multi-regression approach improves the proportion of variance explained and gives statistically significative results in region where the single regression is not statically significant.

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The multi-regressive approach shows the added value of considering the interplay of different bioclimatic indices in explaining the overall variability of productivity. The possibility of using bioclimatic indicators as a proxy for grape productivity provides a simple tool that grape growers, wine consortia and policy makers can use to adapt to future climate.

0. Introduction

Viticulture is tightly dependent on weather and climate. Over the centuries, winegrowers have adapted to climatic conditions and found the best practices to successfully grow vines in different geographical areas. However, this equilibrium between climate and viticulture could be challenged by climate change (Palliotti et al., 2018). As highlighted by Monteleone et al., 2022, climate change has been considered in different studies in the assessment of crop vulnerability. The impact of climate variability and change on grapes has been the subject of many studies, showing how rising temperatures and changing rainfall patterns can affect grape growth (Droulia and Charalampopoulos, 2021; Jones, 2007; Jones, 2003; Lena et al., 2012; Schultz, 2016). Temperature is the main driver for phenology (De Cortázar-Atauri et al., 2017) and a warmer climate may lead to an anticipation of the phenological phases and to a shortening of the growing cycle, which influence the quality of the harvest (Bock et al., 2013; Koufos et al., 2022). A change in the life cycle timing also increases frost risk, as budburst occurs earlier, when frost events are still likely to occur (Mosedale et al., 2015; Sgubin et al., 2018), while variations in the precipitation pattern can increase the exposure to pest and diseases (Bois et al., 2017). Furthermore, important shifts in viticulture suitability are expected in many traditional wine-producing regions, including Italy, that can lead to a decline in production (Hannah et al., 2013; Sgubin et al., 2023; Moriondo et al., 2013).

In Italy, wine represents the second most important exported product within the national agri-food sector, valued 7 billion euros in 2021, growing by 12.4 % compared to 2020 and 51.5 % compared to 2012 (Del Bravo et al., 2022). With almost 10 % of the world area devoted to wine production, Italy has been in 2022 the first wine producer in the world (49.8 million hectolitres), followed by France (45.6 Mio hl) and Spain (35.7 Mio hl) (OIV, 2023).

Italian viticulture is a complex mosaic of appellation laws, driven by different climatic and environmental conditions and characterised by different vineyard management and resource optimisation strategies (Miglietta and Morrone, 2018). From a climatic point of view, Italy is classified as hot summer Mediterranean climate (Koppen-Geiger classification by Beck et al., 2018), with dry summers and wet winters, but the southwest is characterised by dryer conditions, especially inland, while the northeast is wetter and the complex orography can be characterised by very cold conditions (Fratianni and Acquaotta, 2017). Consequently, each region implements different cultivation styles, selected according to the needs of the area and the local climate. Thanks to this heterogeneity, Italy exhibits a high cultivar diversity hosting the top 80 most cultivated grape varieties (OIV, 2017). For premium wines in particular, the link between the type of wine produced and the home territory is of paramount importance, in terms of the grape variety selected, the soil property and viticultural practices used. This link is reflected in detailed specifications for vintage management and winemaking techniques (Gori and Alampi Sottini, 2014; Meloni et al., 2019).

Being part of the Mediterranean region, Italy is a climate hotspot, i.e., a region where the impact of ongoing and future climate change on the environment and human activities are expected to be particularly severe (Giorgi, 2006; Lionello and Scarascia, 2018; Tuel and Eltahir, 2020). In the past 20 years, European winegrowers already experienced the effect of higher temperatures and more frequent drought conditions on their activity. Those effects include variation in harvestable quantities, increase of pests and diseases, changes in phenology, increase in frost risk (Di Carlo et al., 2019; Van Leeuwen et al., 2019). In Italy the main effects reported are a decrease in quantity, an increase in diseases but also a higher wine quality (Battaglini et al., 2009). However, other factors, besides climate variability and change, can impact on wine production and productivity. The market can influence the choice of cultivars towards more profitable varieties, while viticultural practice can play a major role in ensuring a steady yield through the years (Basso, 2019; Vinatier and Arnaiz, 2018). The most common adaptation strategies implemented to cope with the adverse effects of climate, are changes in rootstock, in pruning techniques and/or soil management that together with irrigation are useful against sunburn and heatwaves (Fraga, 2019; Keller, 2010). Also, the selection of new varieties can improve the drought resistance (Hayman and Longbottom, 2012), however the application of such a strategy in Italy would require a modification of the denomination law. Despite the possible adaptation strategies, a rapid change in climate conditions could place a strong risk on the sector especially in Italy, and winegrowers are calling for more reliable local information on future impacts of climate change on viticulture (Battaglini et al., 2009; Moriondo et al., 2011; Mozell and Thachn, 2014). Several approaches have been proposed to answer their call (Ferrise et al., 2016; Sgubin et al., 2023). The most common is based on bioclimatic indices developed from climate variables for specific plants and crops to effectively describe the plant-climate interactions (Santillán et al., 2020; Santos et al., 2020; Santos et al., 2019; Teslić, 2018). The International Organisation of Vine and Wine (OIV) suggests a range of bioclimatic indices tailored to viticulture, based on temperature and heat accumulation (OIV, 2015; OIV, 2012). In addition, Badr et al. (2018), considering the work of (Blanco-Ward et al., 2007), suggest the use of precipitation-based. Bioclimatic indices are often used to assess a region's suitability for viticulture or for zoning purposes (Cardell et al., 2019; Irimia et al., 2013; Koufos et al., 2018; Mavromatis et al., 2022; Santos et al., 2012), but also used in relation with phenology and alcohol concentration (Dalla Marta et al., 2010; Teslić et al., 2018). To assess the impact on climate change and variability, bioclimatic indices are often analysed in correlation with specific phenological phases or harvest dates (Koufos et al., 2014). However, these types of datasets do not give indication on productivity. Alternatively phenological or crop models (e.g. Andreoli et al., 2019; Bonfante et al., 2017; Brisson et al., 2003) can be used to determine the wine production from climate variables, but their calibration requires a huge amount of input data (atmospheric variables minimum and maximum temperatures, radiation and rain-fall, soil hydrology and composition, variety characteristics, vineyard management information etc.) and thus the scalability of their results is limited. Fraga et al. (2012) and Santos et al. (2011) proposed a different approach developing complex statistical tools to estimates yield under present and future climate conditions for a small area in the Douro region.

This study aims to bring new insight on the link between climate and grape production developing a simple statistical model that could support winegrowers in adapting to climate change. The present work focuses on Italy, at NUTS2 (Nomenclature of territorial units for statistics, level 2) scale, and specifically links grape productivity data (q/ha) for wine production with wine-relevant bioclimatic indices. To the best of the author's knowledge of the existing literature, this is a new application of bioclimatic indices and offers a viable alternative to the use of phenological information or harvest dates to assess the impact of climate variability and change on viticulture. Single and multi-regressive approaches are used to determine to which extent bioclimatic indices can explain the changes in Italian grape productivity over time at regional scale. The investigation is conducted on the raw data and on the high frequency component of the time series (i.e., interannual), to assess the impact of both climatic trends and interannual climate variability. The proposed methodology can be easily applied in other countries and used to predict changes in wine productivity under future climate scenarios. In addition, it can represent the base for developing new climatic services and parametric insurance models (Cesarini et al., 2021).

1. Data and methods

1.1. Grape productivity data

The Italian National Institute of Statistics (ISTAT) collects yield data for several agricultural activities in freely available yearly publications; For the wine industry, ISTAT provides the amount of grape harvested for wine production (in quintals) and the extension of the vineyards (in hectares) from 1980 onwards. For the period investigated here, i.e., 1980–2019, the data are not homogenous over time in terms of spatial aggregation. Between 1980 and 1993, and from 2006 to 2019, grape yield data are provided at provincial level (NUTS3), from 1994 to 2000 at regional level (NUTS2), and from 2000 to 2005, at national level only (NUTS0). Thus, data have been homogenised on a spatial aggregation maximizing the temporal coverage. The national scale is discarded since it cannot properly account for the geographical variability of viticulture in Italy. Moreover, with only one harvest a year, the NUTS3 time series is too short (13 years) for the purposes of this study. Therefore, the NUTS2 resolution is chosen for the following two reasons: first, it is the best compromise between temporal coverage and spatial aggregation given the dataset characteristics (i.e., it allows the longest possible time series), and secondly because viticultural policies are regulated at regional level. Thus, when NUTS2 data are not available, the quintals of grape harvested, and the hectares devoted to vineyards provided at NUTS3 level are aggregated to NUTS2 level by computing the yearly sum of the provinces within the same region for the periods 1980–1993 and 2006–2019. This operation produces a NUTS2-aggregation time series covering the periods 1980–2000 and 2006–2019 (35 years), which can frame the spatial variability of grape productivity with enough detail, partially considering local policies and viticultural practice. Grape productivity, here defined as grape yield (q) over hectares of vineyards, is used to investigate the impact of climate on wine production. Employing productivity instead of grape production allows the analysis to be independent from the changes in vineyard area.

1.2. Bioclimatic indices

An overview of the bioclimatic indices used in this study, with their formulas and acronyms, is presented in Table 1. Following the OIV recommendations, five indices based on temperature are selected:

1. Mean temperature during vegetation period (TmVeg): daily mean temperature between 1st April to 31st October (Jones et al., 2005). The growing-season temperature plays a key role in determining the timing of the phenological phases with higher TmVeg leading to an anticipation of the phenological cycle (Malheiro et al., 2013). TmVeg temperatures above 24 °C and below 13 °C are classified as unfavourable for vine cultivation (Eccel et al., 2016).
2. Heliothermic Huglin index (HI): calculated as daily average between mean and maximum temperatures, relative to the baseline temperature of 10 °C, when positive, otherwise equal to zero. Then the sum over the period 1st April - 30th September is corrected by a coefficient of day duration. The 10 °C temperature commonly defines the physiologically active state of the vine, i.e., the baseline temperature at which the vine begins its growth cycle (Huglin, 1978). Higher HI allows increased sugar content in the grapes, which can be desirable depending on the wine type. A climate with HI above 3000° day is classified as "very warm" and is associated to plant stress (Tonietto and Carbonneau, 2004) that, in turn, can lead to a reduction in production. Similarly, HI below 1200° day is considered "too cold" for vine growth (Tonietto and Carbonneau, 2004).
3. Winkler degree days (WI): sum of daily mean temperatures above 10 °C from 1st April to 31st October. WI provides information about the heat accumulation during the growing season (Amerine and Winkler, 1944; Piña-Rey et al., 2020). Analogous to HI, its values are connected to the rate of vine growth and the development of the fruits. In this case the "too hot" ("too cold") threshold is suggested above 2700 (below 850) degree day (Eccel et al., 2016).
4. Biologically Effective Degree Days (BEDD): sum of daily mean temperatures between 10 °C and 19 °C from 1st April to 31st of October. Like WI and HI, BEDD uses a baseline temperature of 10 °C for plant growth, but adds a cut-off at 19 °C, above which additional growth is unlikely to happen (Gladstones, 1992). Values of BEDD higher than 2000 and below 1000° day can negatively influence productivity. Gladstones (1992, 2011) proposed to adjust this index based on a daylength/latitude related factor as well as a daily temperature range factor to account for photosynthetic activity duration of grapevine. A simple version of the BEDDs is used here, with only the 19 °C cut-off used, since the focus here is primarily on time related change of climate (and therefore the effect of latitude is small), and the BEDDs were only slightly affected when the daily temperature range was used.
5. Cool Night Index (CNI): average minimum air temperature in September. The CNI is supposed to relate to the grape's quality (Tonietto and Carbonneau, 2004), where high night temperature in September might lead to lower anthocyanin levels in grapes (Moriondo et al., 2011). Low temperature during harvest period also

Table 1
Acronyms and formulas of the bioclimatic indices used in this study.

	Definition	Formula	Suitable class range
Temperature-based	Mean temperature during vegetation period (TmVeg)	$TmVeg = T_{mean}$ between 1st April to 31th October	13–24 °C (Eccel et al., 2016)
	Heliothermic Huglin index (HI)	$\mathrm{HI} = \mathrm{K} \sum_{01\ \mathrm{Apr}}^{30\ \mathrm{Sep}} max\left[\left(\frac{(T_{mean}-10)+(T_{max}-10)}{2}\right);0\right]$ K = 1.04 length of days coefficient	1200–3000 °C (Tonietto and Carbonneau, 2004)
	Winkler degree days (WI)	$WI = \sum_{01\ Apr}^{31\ Oct} max\left[\left(\frac{T_{min}+T_{max}}{2}-10\right);0\right]$	850–2700 °C (Eccel et al., 2016)
	Biologically Effective Degree Days (BEDD)	$BEDD = \sum_{01\ Apr}^{31\ Oct} min\left\{max\left[\left(\frac{T_{min}+T_{max}}{2}-10\right);0\right];9\right\}$	1000–2000 °C (Gladstones, 1992)
	Cool Night Index (CNI)	$CNI = \frac{1}{30} \sum_{01\ Sep}^{30\ Sep} T_{min}$	12–18 °C (Tonietto and Carbonneau, 2004)
Precipitation-based	Growing season precipitation index (GSP)	$GSP = \sum_{01\ Apr}^{30\ Sep} Prec$ Prec: total precipitation	200–600 mm (Badr et al., 2018)
	Spring Rain index (SprR)	$\mathrm{SprR} = \sum_{21\ \mathrm{Apr}}^{21\ \mathrm{Jun}} Prec_{\mathrm{min}}$	–

affects grapes' quality, being quality of paramount importance for wine production, this index is here used in relation to productivity.

Two precipitation-based indices focused on precipitation are also identified:

1. Growing season precipitation index (GSP): rain accumulated from the 1st of April to the 30th of September. The GSP is relevant to assess the risk of grapevine exposure to water stress for not irrigated grapevine as by law in Italy (Blanco-ward et al., 2017; Blanco-Ward et al., 2007; Piña-Rey et al., 2020).
2. Spring Rain index (SprR; Raül Marcos-Matamoros et al., 2020): rain accumulated between the 21st of April to the 21st of June. This measures the spring wetness: dry springs delay vegetative growth, while wet springs induce higher level of vigour in the plant and increase fungal disease risk (Dell'Aquila et al., 2023).

The computation of the bioclimatic indices is based on temperature and precipitation data extracted from the E-OBS dataset, a gridded daily observational dataset based on meteorological stations across Europe (Photiadou et al., 2017; Van Der Schrier et al., 2013). E-OBS data are provided on a regular latitude-longitude grid with spatial resolutions of 0.1° (~11.1 km). The bioclimatic indices are calculated yearly for all E-OBS grid points over Italy below 1300 m s.l.a. Above 1300 m s.l.a., in Italy, there are no vineyards besides the 2.5 ha in the Sila National Park (Calabria) and some tiny parcels in South Tyrol, too small to be relevant for this study. Then the indices are aggregated at the NUTS2 scale by averaging across the E-OBS grid-points within each region. The time series of the bioclimatic indices in Sicilia ends in 2018 (instead of 2019), due to extensive data gaps in the E-OBS dataset, both in temperature and precipitation.

1.3. Methods

1.3.1. Trend analysis

A trend analysis for the bioclimatic indices is performed to assess the evolution of the climatic condition in Italy in the period 1980–2019 (with the exception of Sicilia, where time series cover the period 1980–2018). The analysis is also extended to productivity, production, and vineyard area to frame the state of the business. The non-parametric Mann-Kendall test is used to verify the presence of a trend with a level of significance of 5 % (Hanif et al., 2022; Mann, 1945). Additionally, the magnitude of possible trend is estimated using Sen's slope estimator (Kh Aswad et al., 2020).

1.3.2. Single and multi-regressive approach

For the single-regressive approach, the Spearman correlation coefficient between the time series of individual indices and grape productivity is computed at NUTS2 scale. The threshold for statistical significance is set to 95 %. Then, a multilinear regression ($y = a*\text{Index1} + b*\text{index2} + c*\text{index3}$ etc) analysis is performed to explore the possibility that a combination of indices explains a higher portion of the productivity variability compared to an individual index. The best subsets regression technique is applied at regional level to identify the optimal combination of indices and relative coefficients for the statistical predictive model of grape productivity. This method aims to find the subset of predictors (in this case the bioclimatic indices) that best predicts the outcome variable (productivity) using all the possible combinations of predictors, while removing the irrelevant ones to simplify the model. The validation is based on the k-fold cross validation method that accounts for non-independent predictors (Kassambara, 2017). The data are first randomly divided into k subsets (k-fold) of approximately equal size, with k equals 5. One-fold (10 % of the data) serves as validation set and the remaining folds (90 % of the data) as training set. This procedure is repeated k times; for every iteration, different groups of data serve as training and testing sets, and the mean squared error is computed at each time. The model prediction error, i.e., cross validation error, is computed as the average of all the mean squared errors (James et al., 2021; Kuhn and Johnson, 2013; Wassennan, 2004). When the coefficient of determination, i.e., the adjusted R squared (AdjR^2), indicates a skilful model, the multi-regressive model is used to predict past productivity based on the selected bioclimatic indices. If the Pearson correlation between observed and predicted productivity is significant at the 95th level ($p \leq 0.05$), the variance explained by the multi-regressive model is compared to the maximum variance explained using one index at a time, to evaluate the added value of the multi-regression model compared to the single-regression method.

The above-described analysis is performed first on raw data. Then, to isolate the interannual variability (i.e., the high frequency component) in the time series of both productivity and bioclimatic indices, the linear trend is removed from the raw series when a statistically significant trend is detected. In the time series not showing significant trends, the climatological mean is removed. The comparison of the raw data and the high frequency component correlations allows to determine the fraction of yield variability associated with the long-term trend (and possibly with a climate change signal) and the interannual (i.e., natural) variability, respectively.

2. Results

2.1. Grape productivity in Italy

Fig. 1 shows the most productive areas in terms of (a) average annual productivity and (b) contribution to total Italian wine production. Some administrative regions with quite high average annual productivity, as Abruzzo and Trentino-Alto Adige (ABR, TRA > 100 q/ha), may limitedly contribute (<5 %) to the national production. Vice versa, regions like Sicilia (SIC), show a low productivity, but are major contributors to the Italian wine production (>15 %). This depends on the areas devoted to the vineyards (SIC ~137,000 ha, ABR 36700 ha, TRA 15200), and to the management techniques in place.

Veneto (VEN), Puglia (PUG), Sicilia (SIC), in violet, followed by Emilia-Romagna (*E*-R) in red, are the most important wine producing regions in Italy explaining together more than half of the total national production (Fig. 1b). Other important wine-growing regions are Toscana (TOS), Piemonte (PIE), as well as Lombardia (LOM), well-known worldwide for the quality of their wines. PIE has the highest numbers of appellation of origin (DOC, DOCG) and geographical indications (IGP) in Italy, followed by TOS, VEN and LOM (Sarnari, 2022).

2.2. Trend analysis

Table 2 shows the trend analysis for both bioclimatic indices and productivity. The latter proves to be independent from the changes in vineyard-devoted area. Productivity shows significantly positive trends in Basilicata (BAS), Campania (CAM), Emilia Romagna (*E*-R), Friuli-Venezia Giulia (FVG), Puglia (PUG), Veneto (VEN), and negative only in Sicilia (SIC) and Trentino-Alto Adige (TRA), besides the strong reduction in vineyard area in all Italian regions, except TRA (Table A3). The temperature-based indices reflect in their trends the general temperature increase in Italy reported in literature (Bartolini et al., 2008; Gentilucci et al., 2019; Toreti and Desiato, 2008). Indices including maximum temperature, i.e., BEDD, WI and HI, exhibit strongly positive trends everywhere and significance in almost all regions. On the contrary those based on mean or minimum temperature, although positive in most cases, show small and mainly non-significant slopes, especially CNI index. This is consistent with the more limited warming in autumn and winter observed in southern Europe in the 1985–2010 period (Van Den Besselaar et al., 2015). Precipitation-based indices show a less homogenous picture, but in general characterised by positive and significant trends in the southern Italy, and negative, but mostly non-significant, trends in the central and northern regions.

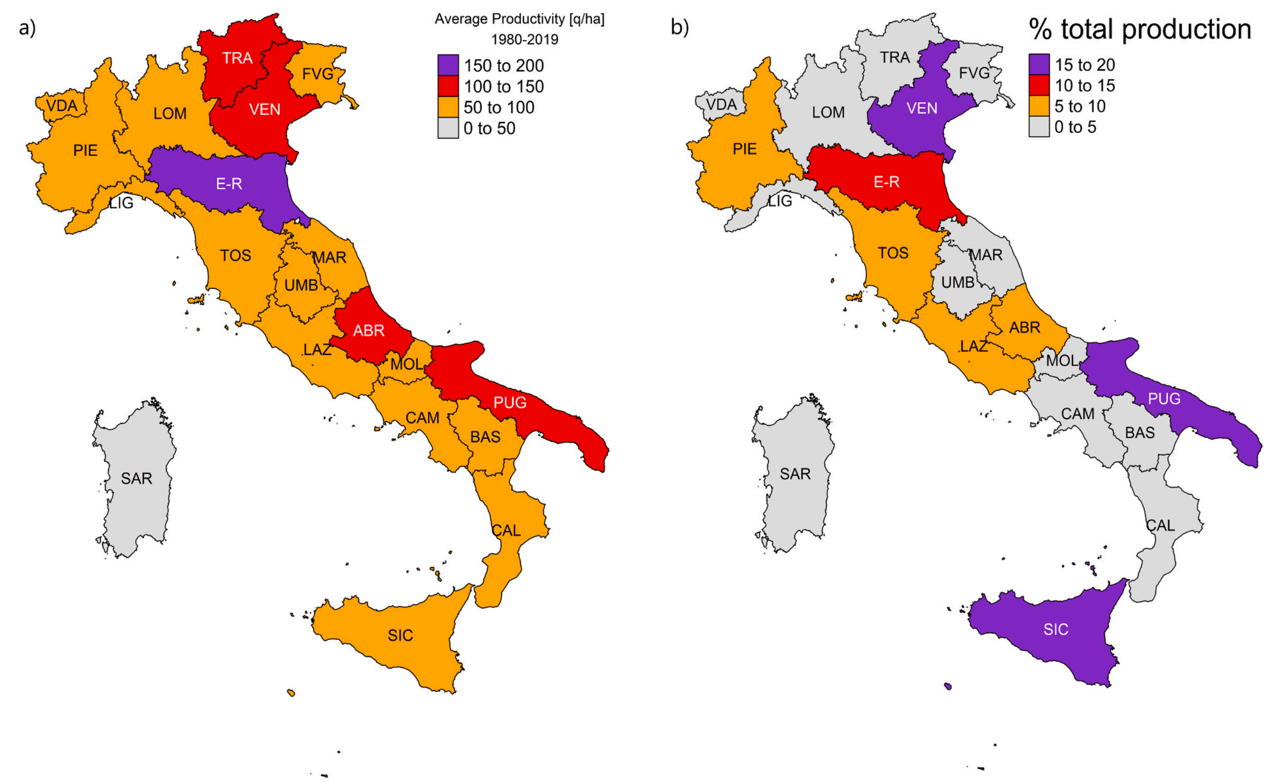

Fig. 1. Map of Italy showing a) yearly average productivity (q/ha) in the period 1980–2019 and b) contribution to the national total production in each region in percentage. The list of regions with their labels is reported in Table 2.

2.3. Climate-productivity relationship

The time series of the bioclimatic indices show values in classes not favourable to grapevine growth for temperature-based indices in 3 regions (out of 20) among those contributing <5 % to the total Italian production (Fig. 1b). Specifically, "too-cold" BEDD values are observed in Friuli Venezia Giulia (FVG), Trentino-Alto Adige (TRA) and Valle d'Aosta (VDA), while HI, WI and TmVeg in the "too-cold" class are found in TRA and VDA (Fig. 1). However, this is not accompanied by a significant decrease in productivity (Fig. A6), indicating on the one hand a high level of local adaptation to unfavourable climate conditions, and on the other hand the need to adapt the existing thresholds to the Alpine regions, like FVG, TRA and VDA. The occurrence of "very cool nights" is widespread in central and northern Italy, while warm nights affect southern regions (Puglia (PUG), Sardegna (SAR) and Sicilia (SIC)) but no statistically significant relationship with productivity can be found for CNI and precipitation-based indices (Fig. A6).

During the four decades analysed, all temperature-based indices show positive correlations with the productivity over Italy, with the exception of a few regions; especially, Sicilia (SIC) is characterised by a strong negative correlation in all cases (Fig. 2). This could suggest that the winegrowing practices have adapted over time to the increasing temperature (Boselli et al., 2016). The strongest and statistically significant correlations are found in the northeast Italy (VEN and E-R) and southern regions (PUG, BAS and CAM), among the regions contributing the most at the national wine production (cf. Fig. 2 to Fig. 1b). In VEN, HI index shows the highest correlation (almost 0.6), explaining up to the 35 % of total productivity variability, while other temperature-indices (BEDD, WI, TmVeg) range from 27 % to 30 % of explained variability. E-R shows positive and significant correlation for BEDD and HI, between 0.35 and 0.39, accounting for up to the 15 % of the total productivity variability. Similar ranges are found for the south of Italy in CAM, while the highest correlations ($\rho = 0.56$) are registered in PUG and BAS, where respectively BEDD and TmVeg explain the 31 % of the productivity variability. The CNI index shows significant correlations of almost 0.4 only for PIE and PUG. This is not surprising since CNI is supposed to relate to grape quality rather than productivity. However, as quality is of paramount importance in the wine sector, the CNI could be indirectly linked to grape productivity since it is common practice to select grapes in the field before harvesting in order to preserve the quality of the final product. SIC stands out, being the only Italian region showing strongly negative and significant correlations for all temperature-based indices, ranging from 0.47 (CNI) to 0.68 (TmVeg), with TmVeg explaining up to 46 % of the productivity variability. Temperature seems to have a strong effect on Sicilian grape productivity and the projected increase in temperature (Bucchignani et al., 2016) could threaten production. SIC is also the only region showing a significant decreasing trend in both productivity and in vineyard-devoted area (Table A3).

Precipitation-based indices show weaker correlation and no clear geographical pattern with respect to temperature-based indices. Statistically significant results both for GSP and SprR are present only in the north-western Italy. Specifically in PIE, where those indices explaining up to 14 % of the variability, negative correlations suggest that an excess of rain is detrimental for the harvest, likely because of the triggering of fungus disease (Gessler et al., 2011; Launay et al., 2014). On the other hand, VDA, which is small contributor to the national wine production, presents positive and high correlations for both indices (ρ up to 0.4). Vineyards here could be less prone to fungus disease given the low temperature of the Alpine area, where VDA is located. However, the results might also be spurious since based on only four grid points given that most of the region lays above 1300 m s.l.a.

Fig. 3a shows the Pearson correlation between the observed productivity and the productivity predicted using the multi-regressive model (coefficients shown in Table A4), highlighting the relevant bioclimatic indices in each region. The model provides statistically significant predictions in 14 out of 20 regions and with correlations above 0.40 in 11 regions out of 20. It well represents the productivity of the biggest contributors to the Italian production, i.e., Veneto (VEN), Sicilia

Table 2
Mann Kendal Z and Sen's Slope of the trend analysis of bioclimatic indices and productivity over the period 1980–2019. The * and bold font mark statistically significative trend ($p \leq 0.05$).

Region	Cod. Reg.	Productivity		BEDD		HI		WI		Tm Veg		CNI		GSP		SprR	
		Z	Sen's Slope [(q/ha) /year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [GDD/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [°C/year]	Z	Sen's Slope [mm/year]	Z	Sen's Slope [mm/year]
Abruzzo	ABR	0.60	0.31	4.86	**5.69***	4.77	**13.25***	4.95	**11.52***	4.95	**0.06***	1.57	0.02	2.73	**2.07***	2.06	**1.48***
Basilicata	BAS	2.45	**0.85***	5.07	**5.15***	3.81	**8.46***	4.98	**10.61***	5.16	**0.05***	3.23	**0.05***	4.47	**2.7***	1.85	1.18
Calabria	CAL	−0.79	−0.05	1.25	1.08	2.26	**2.35***	2.52	**2.4***	2.53	**0.02***	0.90	0.01	2.13	**1.68***	−0.69	−0.4
Campania	CAM	2.27	**0.35***	4.51	**4.71***	3.55	**7.44***	4.21	**9.09***	4.37	**0.05***	2.57	**0.04***	1.83	1.99	1.18	0.72
Emilia Romagna	E-R	2.73	**1.1***	4.07	**3.37***	5.21	**11.97***	4.44	**8.31***	4.60	**0.04***	0.05	0	−0.83	−0.84	0.43	0.23
Friuli Venezia Giulia	FVG	2.23	**0.63***	2.32	**2.01***	4.28	**8.7***	2.88	**3.88***	3.46	**0.03***	0.00	0	−0.98	−0.67	−0.48	−0.62
Lazio	LAZ	−0.57	−0.14	5.14	**4.99***	4.53	**9.8***	4.32	**10.52***	4.43	**0.05***	2.04	**0.04***	−0.13	−0.16	−0.17	−0.16
Liguria	LIG	0.25	0.13	2.85	**3.41***	3.93	**8.64***	2.83	**4.89***	3.33	**0.03***	−2.26	**−0.03***	−1.29	−1.85	−0.76	−1.05
Lombardia	LOM	0.93	0.24	4.74	**4.77***	5.74	**12.15***	5.39	**9.38***	5.51	**0.05***	0.62	0.01	−1.81	−2.4	−1.11	−1.03
Marche	MAR	−1.36	−0.6	2.06	**1.51***	3.02	**7.94***	3.25	**6.71***	3.30	**0.03***	−0.17	0	0.52	0.82	1.99	**1.7***
Molise	MOL	0.37	0.08	4.49	**4.58***	3.41	**8.05***	3.83	**7.68***	4.09	**0.04***	1.22	0.02	3.12	**3.04***	2.67	**1.86***
Piemonte	PIE	1.28	0.14	4.42	**4.6***	5.74	**10.96***	5.38	**7.43***	4.88	**0.04***	−0.98	−0.01	−1.62	−2.33	−1.27	−1.67
Puglia	PUG	2.22	**1.11***	6.65	**3.33***	3.65	**7.62***	5.12	**11.03***	5.20	**0.05***	3.72	**0.07***	4.05	**2.32***	2.64	1.27
Sardegna	SAR	−1.08	−0.22	6.07	**7.5***	4.84	**13.02***	6.62	**14.47***	6.81	**0.07***	2.97	**0.04***	−0.51	−0.59	−1.20	−0.7
Sicilia	SIC	−3.44	**−0.69***	5.76	**6.35***	4.67	**10.51***	5.47	**15.06***	5.43	**0.07***	3.19	**0.04***	2.95	**1.50***	−0.22	−0.07
Toscana	TOS	4.20	**0.4***	0.29	0.53	0.55	1.31	0.92	1.78	0.90	0.01	0.23	0	−1.01	−1.27	−0.38	−0.42
Trentino Alto Adige	TRA	−2.24	**−0.55***	5.32	**5.37***	35.00	**10.88***	5.91	**6.92***	6.33	**0.05***	0.92	0.02	−1.13	−1.78	−1.39	−1.27
Umbria	UMB	1.50	0.38	1.99	**2.29***	1.97	**4.89***	2.20	**5.47***	2.57	**0.03***	0.47	0.01	−0.44	−0.31	0.20	0.09
Valle d'Aosta	VDA	−1.58	−0.25	5.39	**7.05***	6.55	**12.22***	5.89	**7.91***	5.24	**0.06***	0.00	0	−3.42	**−2.72***	−1.46	−1.26
Veneto	VEN	3.27	**1.03***	4.56	**5.04***	5.49	**13.6***	5.09	**9.4***	5.12	**0.05***	0.38	0.01	−1.92	−1.17	−0.46	−0.57

(SIC) and Puglia (PUG), with significant correlation between 0.45 and 0.52 and performs equally well in regions like Piemonte (PIE) and Lombardia (LOM) known worldwide for the quality of their wines. The regions where the multi-regression model has no skill (i.e., low adjR^2) are Toscana (TOS), Marche (MAR) and Abruzzo (ABR) (in grey), while is not significant in Umbria (UMB) Lazio (LAZ) and Valle d'Aosta (VDA). These regions do not show a significant correlation even with the single regression model. Several reasons could explain this result: climate may have a relatively low effect on vine growth, at least for the time being, other bioclimatic indices may be better suited for these regions; or local management practices have successfully adapted to mitigate the effects of climatic changes. Other types of intervention could also explain the lack of correlation, such as planting vineyards with more productive grape varieties, or the emergence of premium red wine, which favours grape production with a limited yield (Mannini, 2004).

The advantage of the multi-regression model is its ability to account for the interplay of temperature and precipitation-based indices on productivity, while selecting only the most appropriate ones. The multiregressive approach also indicates that precipitation-based indices can be used to correctly predict productivity, while the single-regression model rarely reveals any significant correlation with those indices (Fig. 2). The most remarkable improvements are found in CAL, LOM, MOL and TRA, where the predictive model explains above 30 % of the variance while none of the index alone show significant correlation with productivity (Fig. 3b). Benefits are also significant for FVG (+25.3 %), LIG (+8.7 %) and CAM (+10.9 %) and for regions important for wine production like VEN (+17.1 %), PIE (+5.6 %), and *E*-R (+18.7 %). There is one cases where a worsening of the performance is found in BAS, although the extent of this decrease is <2 %. In conclusion, the multiregressive model substantially increases the total variability in productivity explained by bioclimatic indices in most regions compared to the single-regression approach. Almost a third of the variance in productivity is explained in both the northern and southern regions with peaks of about 50 % in VEN and PUG, others non-climatic factor can contribute to the total variance (i.e., vineyard management, market laws, regulations etc).

2.4. *Climate-productivity interannual relationship*

This section investigates to which extent the bioclimatic indices can explain the variability in productivity at the interannual time scale, starting from a single-regressive approach (Fig. 4). A similar pattern to the long-term changes is observed for both precipitation and temperature-based indices, although the correlations are substantially lower or not significant. This suggests that productivity is less affected by short-term climate fluctuations than by systematic changes with few exceptions. In LIG the temperature-based indices HI and WI show a statistically significant correlation at interannual time scale, explaining respectively the 13 % and 12 % of the productivity total variance. To note that HI shows a significant (positive) correlation also in the raw data, while WI does not (Fig. 2 vs Fig. 4). This indicates that LIG productivity is sensible to HI in terms of both its long-term trend and interannual variability, while is affected by the year-to-year variation of WI but not by his trend (Fig. 2). A similar behaviour is observed in TRA for HI and WI that show significant positive correlations with productivity at the interannual time scale, explaining 21 % and 18 % respectively, but not in raw data. CNI in PIE also shows a positive and significant correlation with productivity, thus PIE is sensitive to CNI at both time scales (Fig. 2). Regarding precipitation-based index, there are not significant result at the interannual time scale, suggesting that the year by year changing of precipitation has no impact on productivity.

The multi-regressive model outperforms single-regressive approach finding significant correlations in regions where none of the bioclimatic indices alone can explain the interannual variability in productivity (Fig. 5b). Substantial improvements up to 44 % are found in MOL, and up to 23 % in CAL, VEN and *E*-R. The multi-regression allows an

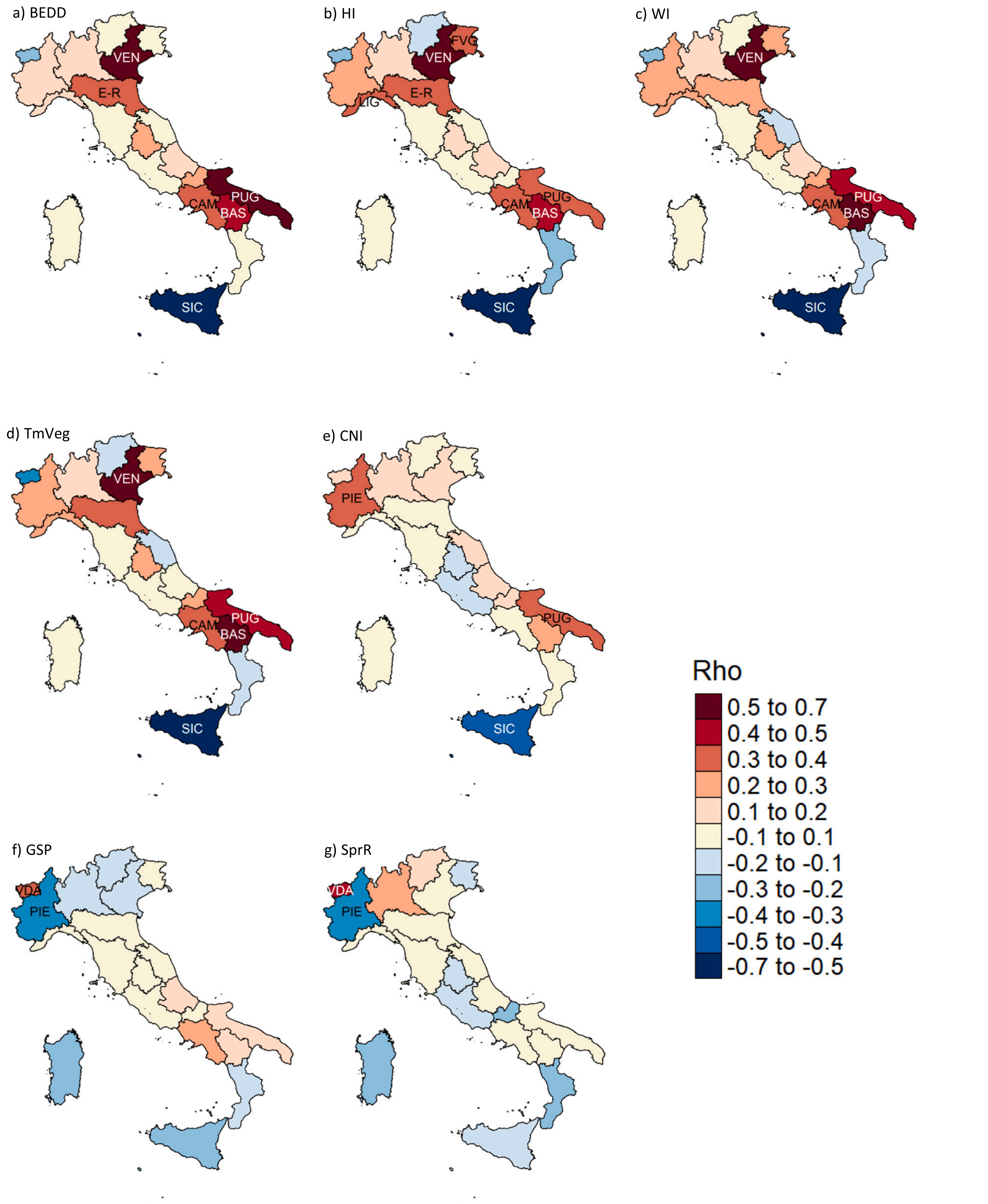

Fig. 2. Maps of Italy showing the Spearman correlation coefficient between the observed productivity and the bioclimatic indices (raw data). The regions where correlations are significant are labelled.

improvement also in LIG (+13 %), and TRA (+33 %).

The multi-regression analysis at interannual time scale provides significant results for 13 regions compared with the 14 obtained in the raw data analysis, and it explains similar portions of the variance. Finally, comparing the two multi-regression analysis (Fig. 5a compared to Fig. 3a), one can notice that most of the regions showing predictability (PIE, LIG, FVG, VEN, E-R, CAM, CAL, SIC, TRA) are sensible to both long-term changes in the bioclimatic indices and their year-to-year variability. Instead, regions like LOM and PUG, are affected only by long-term trend and just UMB is affected only by interannual variability.

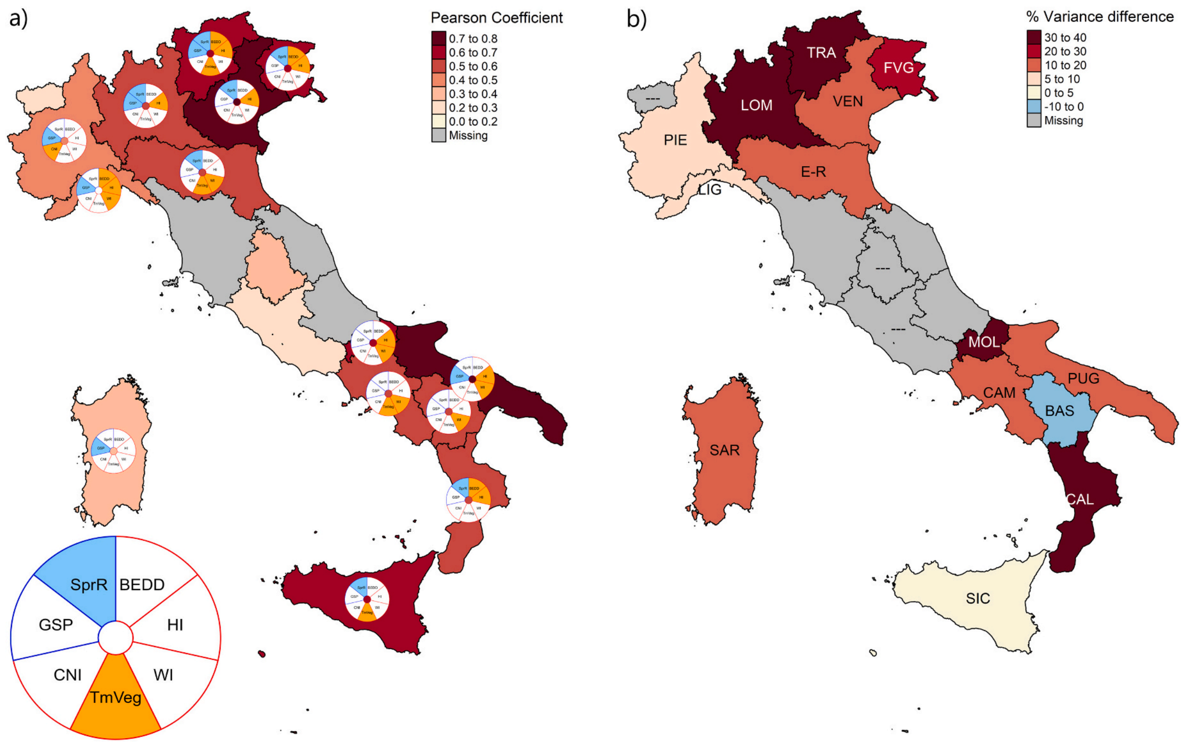

Fig. 3. Maps of Italy showing raw data analysis. a) Pearson correlation coefficient between the observed productivity and the productivity predicted by the multi-regression model. Grey colour represent regions were the multi-regressive model has no skill, i.e. low AdjRˆ2. Donuts are displayed on regions where correlations are significant (p-value ≤ 0.05) and indicate which indices are included in the multi-regression. Within the donuts, orange (blue) colour indicates that temperature-based (precipitation-based) indices are included in the multi-regression model for the specific region, as the example in the bottom left corner shows. b) Difference between the variance explained using the multi-regression model and the maximum variance explained by a single index. Grey colour represent regions where the multi-regression model either has no skill or correlation is not significant (indicated with "—").

3. Discussion

The aim of this study is to explore, for the first time, a direct statistical relationship between the bioclimatic indices commonly used in viticulture and grape productivity in Italy. The research, conducted at the regional scale (NUTS2) in Italy, use 35 years of wine grape productivity data from ISTAT and climate variables from the observational dataset E-OBS. To understand to what extent the selected bioclimatic indices can explain the changes in grape productivity in the past, both single and multi-regressive approaches are investigated. In order to compare the impact of long-term changes and inter-annual variability, the analysis is carried out on both raw data and the data after the removal of long-term tendencies (see e.g. Koufos et al., 2022).

The single-regression approach applied on raw data shows mainly positive correlations between productivity and temperature-based indices, highlighting how vineyard management has adapted over time to the increased temperature. Interestingly, for regions contributing the most to national wine production, like Veneto (VEN), Puglia (PUG) and Emilia-Romagna (E-R), a single index can explain up to 35 % of the variance in productivity. Similar results are found analysing data at interannual time scale, with mostly positive correlations, although the correlations are substantially lower and rarely significant.

In Piemonte (PIE, north-western Italy), negative correlations are found for precipitation-based indices, suggesting that an excess of rain could lead to higher risk of fungus disease such as downy mildew and be detrimental for the harvest. In this region, a strong link between precipitation during spring and downy mildew treatments have been shown also in Salinari et al., 2006. Negative correlations with precipitation-base indices are also found at the interannual time scale in PIE, as well as in southern regions where rainfall is usually scarce, although these correlations are not statistically significant.

Overall, the interannual climate variability impacts less on productivity than the long-term trends. The multi-regressive model, taking advantage from the interplay of temperature and precipitation-based indices, proves to be a powerful tool to predict Italian productivity over most regions, especially for raw data, i.e., for long-term tendencies. The multi-regressive model can explain up to 54 % variability in productivity at interannual time scale in Trentino Alto Adige (TRA), and up to 52 % in Veneto (VEN) and Puglia (PUG) at long term variability. Furthermore, this leads to large improvements in the explained productivity variance (e.g. in Trentino Alto Adige (TRA) the increase is 39 % for raw data, and 44 % in Molise (MOL) at interannual time scale), even when none of the bioclimatic indices alone exhibit significant correlations with productivity. The remaining unexplained variance can depend on other factors than climate that range from viticultural practices to quality of the data collected. A complete picture of all the factors contributing to the total variability require additional investigation and falls out of the scope of this work.

The study highlights the need for better quality data, including its metadata, and the active involvement of local businesses and stakeholders in impact studies to better frame the most relevant issue that they face due to climate variability both in the short- and long- term. In fact, vineyard management, soil type, variety choice, policies and the market can all affect grape productivity, in addition to climate and weather. A limitation of this research is that this information is not included in the ISTAT database.

4. Conclusions

This study investigates the impact of bioclimatic indices on wine grape production in Italy and results in the development of a multi-regressive model to simulate past productivity changes at the regional level. The methodology represents a novelty with regard to the use of bioclimatic indicators, which are most often used to assess regional

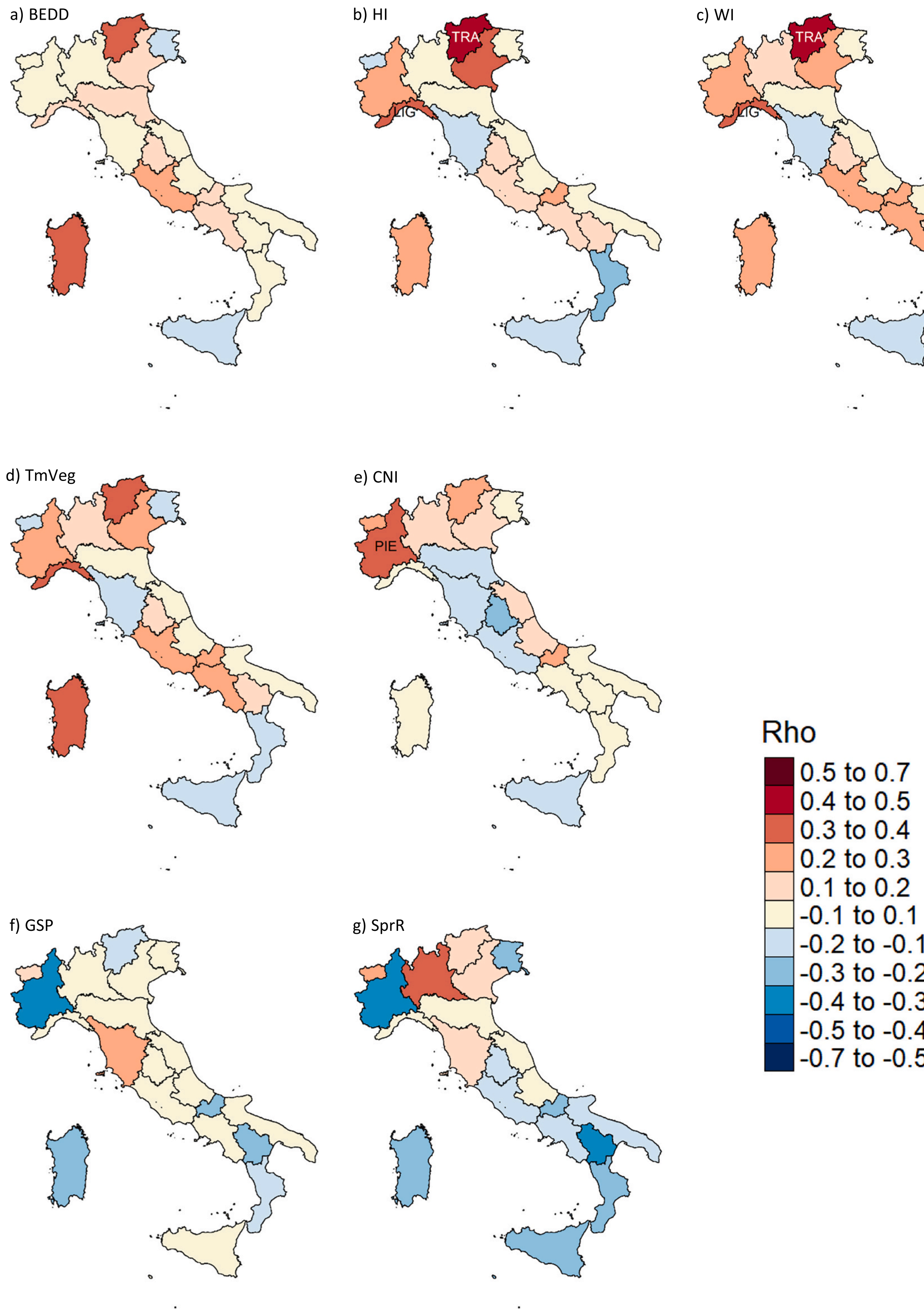

Fig. 4. As Fig. 2, but at interannual time scale. Maps of Italy showing the Spearman correlation coefficient between the observed productivity and the bioclimatic indices (raw data). The regions where correlations are significant are labelled.

suitability for viticulture, but without directly relating them to productivity. The predictive models explain up to 52 % of the historical harvest variability and thus show potential for being a valuable tool to estimate future changes in productivity when used in conjunction with seasonal forecast and/or future climate projections. In addition, the proposed methodology tested for Italy can be easily applied to other countries and regions as well as at local scale. The involvement of wine consortiums could improve quality, resolution and information regarding the data and enhance the knowledge on specific climatic challenges the wineries are facing.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.167134.

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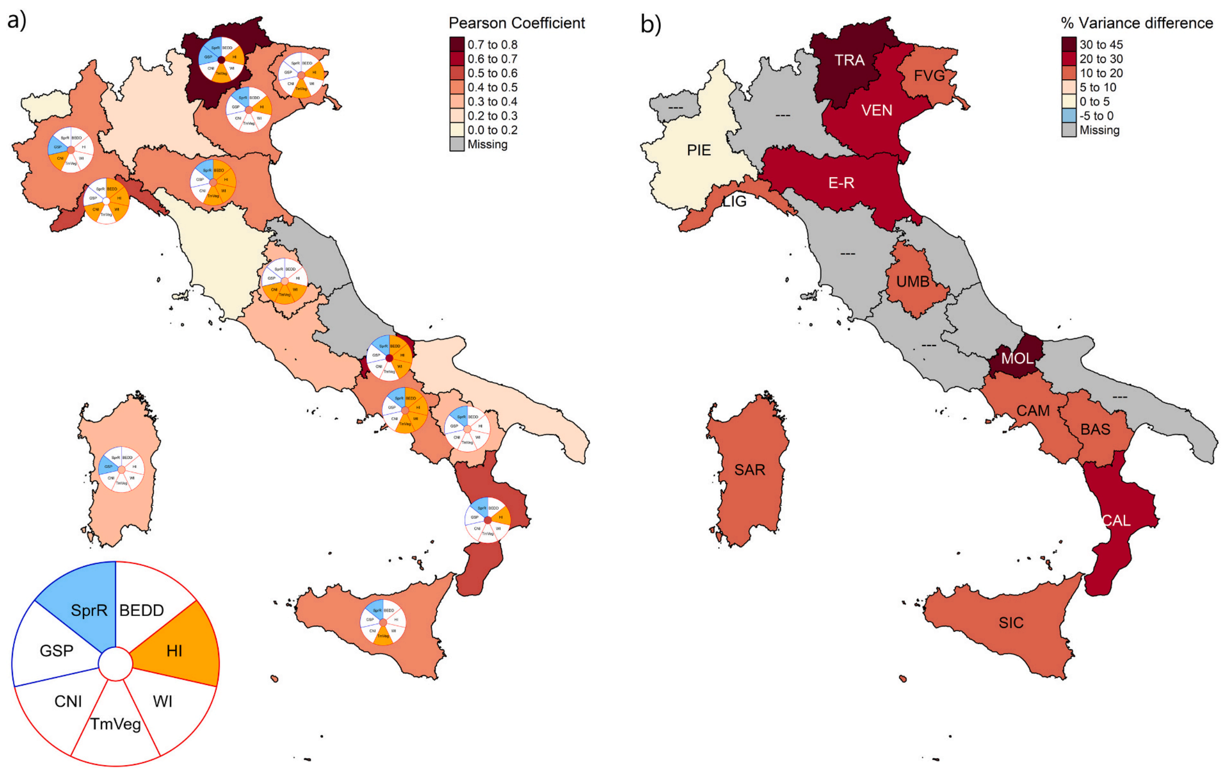

Fig. 5. As Fig. 3 but at interannual time scale. a) Pearson correlation coefficient between the observed productivity and the productivity predicted by the multi-regression model. Grey colours represent regions where the multi-regressive model has no skill, i.e. low AdjR^2. Donuts are displayed on regions where correlations are significant (p-value $\leq$ 0.05) and indicate which indices are included in the multi-regression. Within the donuts, orange (blue) colour indicates that temperature-based (precipitation-based) indices are included in the multi-regression model for the specific region, as the example in the bottom left corner shows. b) Difference between the variance explained using the multi-regression model and the maximum variance explained by a single index. Grey colour represent regions where the multi-regression model either has no skill or correlation is not significant (indicated with "—").

CRediT authorship contribution statement

Laura Massano: Conceptualization, Methodology, Writing – original draft. **Giorgia Fosser:** Methodology, Writing – review & editing, Supervision. **Marco Gaetani:** Methodology, Writing – review & editing, Supervision. **Benjamin Bois:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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APPENDIX B. A LOCAL SCALE ITALIAN STUDY OF THE IMPACT OF CLIMATE VARIABILITY ON WINE GRAPE PRODUCTIVITY USING A CONVECTIVE MODEL

Supplementary data

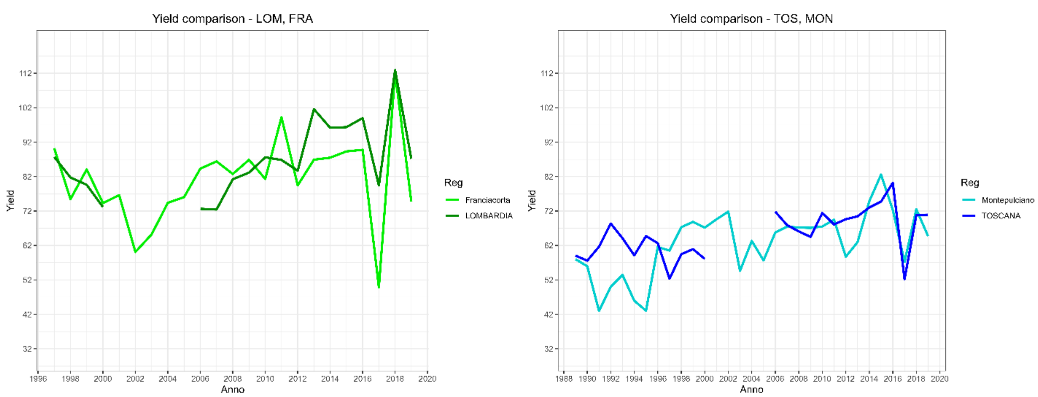

Figure A 2 a) FRA productivity data (1997-2019) calculated by aggregating the Franciacorta DOCG and Curtefranca DOC denominations and the LOM productivity data time series provided by ISTAT. b) MON productivity data (1989-2019) calculated by aggregating the Vino Nobile and Rosso di Montepulciano denominations and the TOS productivity data time series from the ISTAT database.

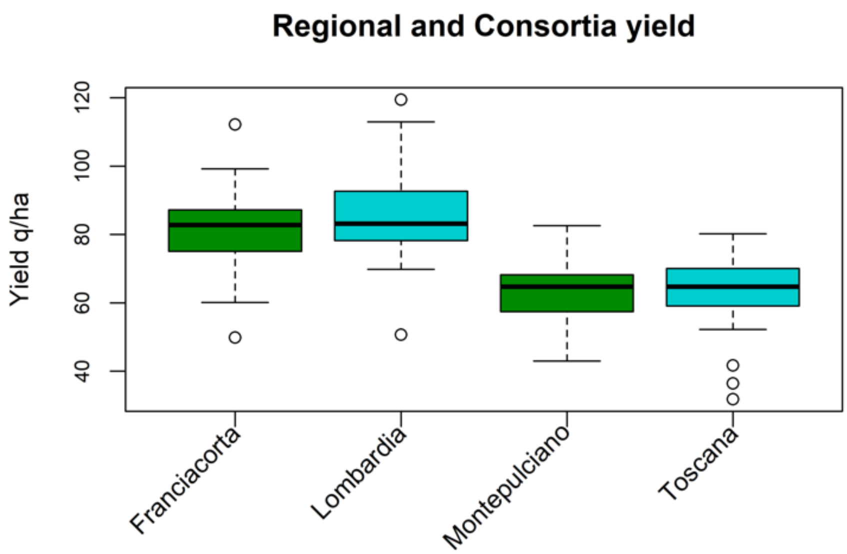

Figure A 3 Boxplot of the regional productivity (cyan) and consortia productivity (green). The series of LOM and TOS come from ISTAT database and cover the period 1980-2019, whit a six-year gap between 2000-2005, the period available for FRA is 1997-2019 (calculated by aggregating the Franciacorta DOCG and Curtefranca DOC denominations) and for MON is 1989-2019 (calculated by aggregating the Vino Nobile and Rosso di Montepulciano denominations), with no gap in the series.

Table A 4: results of Welch's t test and temporal correlation between regional ad consortia productivity data. The * symbol indicate a statistically significant results (p<=0.05), the degrees of freedom (DoF) for the t test based on the number of observations are computed according to the Welch's equation for effective degrees of freedom (Welch, 1947).

Consortium	*t.stat*	*t.tab*	*DoF*	*Cor.Coef.*
FRA	1.17	2.01	47.94	0.62*
MON	0.1	2	63.99	0.55*

Table A 5: Spearman correlation coefficient (ϱ) and root mean squared error (RMSE) between SPHERA (E-OBS) and CPM, as well as SPHERA (E-OBS) and RCM time series in the FRA and MON area.

FRA								
	TM		TX		TN		P	
	ϱ	RMSE (°C)	ϱ	RMSE (°C)	ϱ	RMSE (°C)	ϱ	RMSE (mm)
SPHERA CPM	**0.95***	0.78	**0.94***	1.54	**0.96***	0.39	**0.84***	233.52
SPHERA vs RCM	**0.95***	0.38	**0.96***	1.73	**0.91***	1.37	**0.73***	415.05
E-OBS vs CPM	**0.76***	0.64	**0.78***	0.6	**0.55***	0.78	**0.76***	435.99
E-OBS vs RCM	**0.85***	0.37	**0.82***	0.43	**0.58***	0.61	**0.77***	266.65
MON								
	TM		TX		TN		P	
	ϱ	RSME (°C)	ϱ	RSME (°C)	ϱ	RSME (°C)	ϱ	RSME (mm)
SPHERA CPM	**0.79***	1.06	**0.81***	1.15	**0.78***	0.58	**0.78***	196.26
SPHERA vs RCM	**0.86***	0.91	**0.92***	1.66	**0.77***	0.77	**0.78***	133.12
E-OBS vs CPM	0.16	0.79	**0.65***	0.85	-0.08	1.39	**0.86***	177.98
E-OBS vs RCM	0.06	0.83	**0.52***	0.57	0.04	0.94	**0.8***	128.03

Table A 6: Welch's t-test between SPHERA (E-OBS) and CPM, as well as the SPHERA (E-OBS) and RCM time series in the FRA and MON. For each variable (TM,TX,TN and P) the test statistics (t.stat), the t tabulated or critic (t.tab) for a 95% confidence interval and the degree of freedom (Dof) computed using Welch's formula are reported. Bold font and an asterisk (*) indicate a significant p-value of <= 0.05, indicating the rejection of the null hypothesis (h0) and a statistically significant difference between the series.

FRA												
	TM			TX			TN			P		
	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof
SPHERA vs CPM	**4.16***	2.03	35.2	**6.7***	2.03	34.25	**-2.31***	2.03	35.96	**-2.07***	2.03	35.85
SPHERA vs RCM	1.8	2.03	34.77	**7.77***	2.03	34.83	**-8.26***	2.03	35.59	**-4.48***	2.03	35.47
E-OBS vs CPM	**2.98***	2.03	33.1	-1.54	2.03	35.76	**3.84***	2.03	36	**4.93***	2.04	29.22
E-OBS vs RCM	0.5	2.04	32.45	-0.75	2.03	35.95	**-2.24***	2.03	35.83	**2.91***	2.04	32.58
MON												
	TM			TX			TN			P		
	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof
SPHERA vs CPM	**6.45***	2.03	35.57	**5.24***	2.03	35.97	**3.38***	2.04	32.37	**2.33***	2.03	35.69
SPHERA vs RCM	**5.72***	2.03	35.03	**8.15***	2.03	35.83	**-4.8***	2.04	32.12	1.3	2.03	35.91

E-OBS vs CPM	-0.24	2.04	30.12	**-3.29***	2.03	35.99	**4.89***	2.06	24.89	**2.37***	2.03	35.57
E-OBS vs RCM	-0.95	2.04	29.09	-0.81	2.03	35.76	-0.87	2.06	24.71	1.34	2.03	35.96

Table A 7 :Welch's t-test between SPHERA (E-OBS) and CPM, as well as the SPHERA (E-OBS) and RCM time series in the FRA and MON. For each bioclimatic index the test statistics (t.stat), the t tabulated or critic (t.tab) for a 95% confidence interval and the degree of freedom (Dof) computed using Welch's formula are reported. Bold font and an asterisk (*) indicate a significant p-value of <= 0.05, indicating the rejection of the null hypothesis (h0) and a statistically significant difference between the series.

FRA													
	SPHERA vs CPM			SPHERA vs RCM			E-OBS vs CPM			E-OBS vs RCM			
Index	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	Index
BEDD (GDD)	-0.92	2.03	35.97	-0.17	2.03	35.97	0.67	2.03	35.36	1.47	2.03	35.35	BEDD (GDD)
HI (GDD)	**-4.50***	2.04	32.50	**-4.71***	2.03	33.34	-0.88	2.04	32.14	-0.96	2.03	33.01	HI (GDD)
WI (GDD)	**-4.48***	2.04	32.68	**-4.13***	2.04	32.65	**-3.25***	2.04	30.29	**-2.89***	2.04	30.26	WI (GDD)
TmVeg (°C)	**-4.59***	2.04	32.60	**-4.17***	2.04	32.59	**-3.28***	2.04	30.54	**-2.85***	2.04	30.53	TmVeg (°C)
TnVeg (°C)	**2.86***	2.03	32.92	**5.35***	2.03	35.87	-0.16	2.04	30.41	**2.42***	2.03	34.63	TnVeg (°C)
TxVeg (°C)	**-8.32***	2.03	32.82	**-8.62***	2.03	35.95	**-5.47***	2.04	30.10	**-5.30***	2.03	34.76	TxVeg (°C)
CNI (°C)	0.99	2.03	33.37	**2.29***	2.03	35.16	-1.22	2.03	33.70	-0.11	2.03	35.37	CNI (°C)
TnRest	-0.23	2.03	35.51	**2.69***	2.03	35.40	**-2.53***	2.03	35.77	0.15	2.03	35.84	TnRest
GSP (mm)	**5.55***	2.03	35.93	**8.76***	2.03	33.94	**-4.23***	2.04	32.17	-1.48	2.03	35.20	GSP (mm)
SprR (mm)	-0.03	2.03	36.00	1.92	2.03	35.18	**-3.80***	2.04	31.84	-1.86	2.03	34.38	SprR (mm)
MON													
	SPHERA vs CPM			SPHERA vs RCM			E-OBS vs CPM			E-OBS vs RCM			
Index	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	Index
BEDD (GDD)	**-2.25***	2.03	35.88	**-2.13***	2.03	35.84	1.91	2.03	34.16	**2.04***	2.03	34.04	BEDD (GDD)

HI (GDD)	-3.31*	2.03	34.11	-3.71*	2.03	35.41	-1.37	2.03	33.35	-1.65	2.03	34.90	HI (GDD)
WI (GDD)	-5.21*	2.03	34.38	-5.66*	2.03	35.53	-2.14*	2.03	36.00	-2.37*	2.03	35.56	WI (GDD)
TmVeg (°C)	-5.38*	2.03	34.59	-5.79*	2.03	35.61	-2.06*	2.03	35.96	-2.24*	2.03	35.38	TmVeg (°C)
TnVeg (°C)	-0.54	2.03	35.91	2.90*	2.03	35.78	-1.35	2.03	33.90	1.70	2.03	33.44	TnVeg (°C)
TxVeg (°C)	-5.43*	2.03	35.98	-5.36*	2.03	35.06	-3.74*	2.03	35.86	-3.57*	2.03	34.60	TxVeg (°C)
CNI (°C)	-1.61	2.03	33.38	0.98	2.03	34.58	-3.31*	2.03	34.96	-0.92	2.03	35.70	CNI (°C)
TnRest	-2.27*	2.03	35.17	-0.82	2.03	34.45	-2.35*	2.03	33.56	-1.01	2.04	32.57	TnRest
GSP (mm)	-1.05	2.04	31.29	2.46*	2.03	35.02	-3.06*	2.05	26.93	-0.04	2.03	35.74	GSP (mm)
SprR (mm)	-2.44*	2.05	27.64	-0.44	2.04	31.33	-2.75*	2.04	32.09	-0.95	2.03	35.18	SprR (mm)

Table A 8: Sen's slope FRA, bold font, and asterisk (*) indicate a significant trend (p<=0.05)

FRA	TM (°C/yr)	TX (°C/yr)	TN (°C/yr)	P (mm/yr)	BEDD (GDD/yr)	HI (GDD/yr)	WI (GDD/yr)	TmVeg (°C/yr)	TnVeg (°C/yr)	TxVeg (°C/yr)	CNI (°C/yr)	TnRest (°C/yr)	GSP (mm/yr)	SprR (mm/yr)
E-OBS	**0.05***	0.05	**0.06***	-5.91	**4.59***	**14.96***	11.67	**0.06***	0	0.1	0.09	0.03	-4.77	-1.33
SPHERA	0.04	0.03	**0.04***	12.89	4.5	9.25	6.65	0.04	0.02	0.05	0.1	0.02	**13.32***	**4.57***
CPM	0.04	0.03	0.04	6.54	3.35	13.34	12.61	0.06	0.01	0.12	**0.13***	0.05	-1.31	0.7
RCM	**0.05***	0.04	**0.04***	-2.14	4.19	11.51	11.94	0.06	**0.05***	**0.12***	0.12	0.07	-2.41	-0.15

Table A 9: Sen's slope productivity FRA bold font, and asterisk (*) indicate a significant trend (p<=0.05)

FRA	Productivity (q/ha)/yr
slope	**1.28***

Table A 10:Sen's slope MON, bold font, and asterisk (*) indicate a significant trend (p<=0.05)

MON	TM (°C/yr)	TX (°C/yr)	TN (°C/yr)	P (mm/yr)	BEDD (GDD/yr)	HI (GDD/yr)	WI (GDD/yr)	TmVeg (°C/yr)	TnVeg (°C/yr)	TxVeg (°C/yr)	CNI (°C/yr)	TnRest (°C/yr)	GSP (mm/yr)	SprR (mm/yr)
E-OBS	**-0.07***	0.04	**-0.11***	8.64	**-7.89***	1.23	**-17.42***	**-0.08***	-0.09	0.07	-0.07	0.03	4.38	0.07
SPHERA	0.03	0.01	**0.03***	**19.47***	2.94	5.05	7.22	0.03	**0.1***	**-0.08***	**0.12***	0	**10.36***	0.99
CPM	0.03	0.02	**0.03***	5.28	2.42	6.84	3.68	0.02	**0.05***	**0.05***	0.15	0	0.74	1
RCM	0.04	0.03	**0.03***	6.28	1.2	10.5	9.31	0.04	**0.06***	0.01	**0.11***	0.06	-0.08	0.34

Table A 11: Sen's slope productivity MON, bold font, and asterisk (*) indicate a significant trend (p<=0.05)

MON	Productivity (q/ha)/yr
slope	0.43

Table A 12: ranking of the maximum variance (%) explained for each dataset divided by consortia, whit the indication of type of method used (SR: single regression, MR multi-regression)

FRA			MON		
Model	var.value %	type	Model	var.value %	type
RCM	64 %	MR	CPM	45 %	MR
SPHERA	56 %	MR	E-OBS	44 %	SR
CPM	48 %	MR	SPHERA	42 %	MR
E-OBS	42 %	SR	CPM	34 %	SR
SPHERA	36 %	SR	RCM	32 %	SR
E-OBS	35 %	MR	E-OBS	32 %	MR
RCM	35 %	SR	RCM	29 %	MR
CPM	34 %	SR	SPHERA	21 %	SR

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Using a convection-permitting climate model to predict wine grape productivity: two case studies in Italy

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Abstract. Viticulture is tied to climate, it influences the suitability of an area, yield and quality of wine grapes. Therefore, traditional wine-growing regions could be threatened by a changing climate. Italy is at-risk being part of the Mediterranean climatic hotspot and judged in 2022 the second-largest exporter of wine worldwide. The article explores the potential of climate models to predict wine grape productivity at local scale. To this end, both single and multi-regression approaches are used to link productivity data provided by two Italian wine consortia with bioclimatic indices. Temperature and precipitation-based bioclimatic indices are computed by using the observational dataset E-OBS, the high-resolution climate reanalysis product SPHERA, and both the Regional and the Convection-permitting Climate Model (RCM and CPM). The potential of CPMs to represent the impact of climate variability on wine grape productivity at local scale in Italy is evaluated. The results indicate high correlations between some bioclimatic indices and productivity. Climate models appear to be a useful tool to explain productivity variance, however, the added value of CPM, became evident only when precipitation-based indices are considered. This assessment opens the path for using climate models, especially at convection-permitting scale, to investigate future climate change impact on wine production.

1 Introduction

Wine-growing has a strong socio-economic impact and is one of the principal agricultural economic activities in Italy, that in 2022 was the world's leading wine producer (49.8 million hl), and second largest wine exporter, with a value of 7.8 billion euros.

Climate plays a significant role in viticulture, determining the suitability of an area and influencing wine grape yield and quality. Over the coming decades, the wine sector is expected to be affected by climate change especially in Italy that is part of the Mediterranean climatic hotspot (Tuel and Eltahir, 2020), where the impact of climate change is expected to be more severe than the global average (Bernetti et al., 2012; Sacchelli et al., 2016). In this context, many studies investigated the impact of rising temperatures and changing rainfall patterns on grape growth (Bagagiolo et al., 2021; Gentilucci, 2020). Temperature is the primary driver for the phenological phases (Fraga et al., 2016), and a warmer climate may lead to an earlier onset of phenological phases and to a shorter growing cycle, increase frost-related risks, as budburst occurring earlier in spring, when frost events are still frequent (Lamichhane, 2021; Trought et al., 1999). Furthermore, traditional wine-producing regions, as Douro in Portugal, La Rioja in Spain, Bordeaux in

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2 Data and Methods

2.1 Wine grape data

Wine grape yield data, as well as the hectares devoted to viticulture, are collected from two wine consortia in Italy: 'Consorzio per la tutela del Franciacorta' (FRA) and 'Consorzio Del Vino Nobile di Montepulciano' (MON). The first one lies in Franciacorta, a small (200 km2) wine-growing region in Lombardia (LOM), in northern Italy, mostly known for sparkling wine (Figure 1a). The area is characterised by a humid subtropical climate according to the Koppen classification (Costantini et al., 2013). The Iseo lake, located at the northern border of this region, is the sixth largest lake in Italy and tempers the typical heat of the plain in summer, while in winter protects the vineyards from the freezing air arriving from the north (Leoni et al., 2019). The consortium was born in 1990 thanks to the endeavour of local producers that felt the need to preserve the original production method of the Franciacorta wine. Today the consortium is composed by 200 winemakers and preserves three designations: Sebino IGT (Typical Geographical Indication), Franciacorta DOCG (Denomination of Controlled and Guaranteed Origin) and Curtefranca DOC (Denomination of Controlled Origin), known as "Terre di Franciacorta" before 2011 (https://franciacorta.wine/en/). This analysis focuses on the designations of Franciacorta DOCG and Curtefranca DOC from 1997 to 2019 (23 years), discarding Sebino IGT, for which data are only available for a limited period.

a) b)

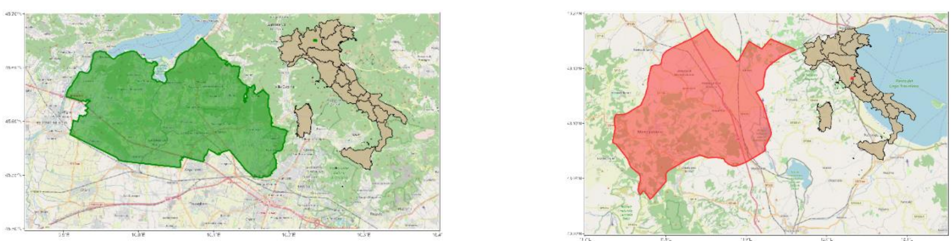

Figure 1 a) Area of Franciacorta Consortium (FRA), Lombardia (LOM) region, North of Italy. b) Area of the Consorzio del Vino Nobile di Montepulciano (MON), Toscana (TOS) region, centre of Italy (base layer : © OpenStreetMap contributors 2019. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.).

The "Consorzio del Vino Nobile di Montepulciano" (MON) (https://www.consorziovinonobile.it/) is located within the Montepulciano territory in Toscana (TOS) region in the centre of Italy (Figure 1b). The area is characterized by a Mediterranean climate with hot and dry summer, and mild and rainy winters (Costantini et al., 2013). The consortium preserves three designations, namely Vino Nobile di Montepulciano DOCG, Rosso di Montepulciano DOC and Vin Santo di Montepulciano DOC. The study focuses on the first two designations that have the longest time series covering 31 years between 1989 and 2019.

For each wine designation, the FRA consortium directly reports the quantity of grapes harvested in quintals (q), while MON indicates the hectolitres of wine produced (hl) and the maximum percentage of the grape yield convertible into wine (70%). For the analysis, the hectolitres are converted into quintals using the maximum percentage allowed, and then the productivity (q/ha) is calculated by dividing the quintals of grapes by the vineyard area.

To check the consistency of productivity data between local and regional scales, and thus contextualise this work within the broader framework of previous studies (e.g. Di Paola et al., 2023), the productivity at the local scales (FRA

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France, and Tuscany in Italy, are expected to experience important shifts in viticulture suitability that can consequently causes a decline in production (Adão et al., 2023; Rafique et al., 2023; Sgubin et al., 2023; Tóth and Végvári, 2016). A common tool to investigate the impact of climate variability and change on the wine sector is the use of bioclimatic indices, developed from climate variables for specific plants and crops (Badr et al., 2018; Chou et al., 2023; Gaitán and Pino-Otín, 2023). A set of bioclimatic indices, based on temperature and heat accumulation (OIV, 2015), was proposed by the International Organisation of Vine and Wine (OIV), while precipitation-based indices were developed by Badr et al., (2018) considering the research of Blanco-Ward et al. (2007). Bioclimatic indices are commonly used to assess a region's suitability for viticulture or zoning purposes, as well as in relation to phenology, harvest date and alcohol concentration (Dalla Marta et al., 2010; Koufos et al., 2014; Sánchez et al., 2019; Teslić et al., 2018). A novel application linking bioclimatic indices directly to wine grape productivity data in Italy was proposed by Massano et al., (2023) at regional level.

In Italy the vineyards are planted in extremely different areas, from the coasts to the hills, in some case also at considerable altitude (Tarolli et al., 2023). The wine production system is complex and fragmented, including both small farms and large companies. To valorise the designation of origin and guarantee a defined level of quality, producers are organized in wine consortia (Consorzi di Tutela) according to the EU and national regulations (e.i. Regulation (EU) No 1308/2013, Disciplinari regionali) (Gori and Alampi Sottini, 2014; Ugaglia et al., 2019). To address this fragmentation and account for the typicity of the wine business (Agnoli et al., 2023; Spielmann and Charters, 2013), yield data from the wine consortia and high-resolution climate data are of prominent importance for local-scale impact studies and, thus for effective adaptation strategies.

In the context of impact studies at local scale, requiring high-resolution climatic data, the use of km-scale convection permitting models (CPM) is increasing (Bamba et al., 2023; Le Roy et al., 2021; Tradowsky et al., 2023). Thanks to their high spatial resolution (less than 4 km), CPMs can represent convection explicitly without the need for parameterisation, thus reducing the associated model uncertainty (Fosser et al., 2024). Compared to coarser resolution regional climate models (RCMs), the CPMs represent more realistically hourly rainfall intensity, the diurnal cycle of precipitation and the extremes and are thus consider more reliable in terms of climate projections of precipitation (Brisson et al., 2016; Coppola et al., 2020; Fosser et al., 2020, 2015; Kendon et al., 2017; Pichelli et al., 2021; Ban et al., 2021). The advantages of CPMs versus RCMs has been also explored in the assessment of the impact of climate change on agriculture and crop production (Agyeman et al., 2023; Berthou et al., 2019; Chapman et al., 2020, 2023). This study assesses the potential of a CPM to represent the impact of climate variability on wine grape productivity at the local scale, by relating temperature and precipitation-based bioclimatic indices to wine productivity data provided by two wine consortia in northern and central Italy. The CPM performance is validated against climate observations and a reanalysis product, as well as compared to the driving RCM simulation to investigate the added-value of the higher resolution. Single and multiple regression approaches are used to determine the extent to which bioclimatic indices can explain changes in wine grape productivity at local scale. The multiple regression approach accounts for the potential interplay between the bioclimatic indices, potentially increasing the portion of total productivity variability explained by the individual indices, as found by Massano et al. (2023).

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and MON) is compared with the productivity at regional scale provided by the Italian National Institute of Statistics (ISTAT). ISTAT provides the harvested wine grape (in quintals) and the area devoted to vines (in hectares) from 1980 onwards. However, the data are not homogenous over time in terms of spatial aggregation. Wine grape productivity data are available at the provincial level between 1980 and 1993 and from 2006 to 2019; at regional level between 1994 and 2000; at national scale while from 2000 to 2005. Following Massano et al (2023), the data were aggregated at regional level for Lombardia (LOM) and Toscana (TOS) region, where the FRA and MON consortia are respectively located, for the period 1980–2019, with a six-year gap between 2000 and 2005. Considering the overlapping periods between ISTAT and consortia time series, it is found that the regional and local productivity data are significantly correlated ($p<=0.05$) for both FRA and MON (Table A 1). In addition, the Welch's t-test proves that both consortium distributions are part of the regional population (Table A 1 and Figure A 1).

2.2 Observational climate data

The observational dataset used is E-OBS, a gridded daily data set covering Europe from January 1950 to the present day. E-OBS is constructed using data from meteorological stations provided by the European National Meteorological and Hydrological Services (NMHSs) or other data holding institutions (Photiadou et al., 2017; Van Der Schrier et al., 2013). The analysis is based on the latest available version (v28) at 0.1 deg (~11 km). Although the E-OBS database is frequently used to validate climate models (Lorenz and Jacob, 2010; Retalis et al., 2016; Christensen et al., 2008; Jaeger and Seneviratne, 2011) , some studies have pointed out limitations in the E-OBS representation of precipitation and temperature, mainly due to the inhomogeneity of the station network used for interpolation (Kyselý and Plavcová, 2010; Van Der Schrier et al., 2013; Liakopoulou and Mavromatis, 2023).
In addition to observations, the analysis uses a high-resolution convection-permitting reanalysis product, called SPHERA (High rEsolution ReAnalysis over Italy; Cerenzia et al., 2022; Giordani et al., 2023), produced by ARPAE-SIMC (Agency for Environmental Protection of the Emilia Romagna Region, Italy). Based on the non-hydrostatic limited-area model COSMO (Schättler et al., 2018; Baldauf et al., 2011), SPHERA dynamically downscales the global reanalysis ERA5 (Hersbach et al., 2020) assimilating regional in situ observations to improve the quality of the simulation. This new reanalysis product covers Italy at a horizontal resolution of 2.2 km with a temporal coverage of 26 years (1995-2020). SPHERA reanalysis, validated against ERA5 by Giordani et al. (2023), shows added value for the description of moderate to severe local precipitation events and extreme rainfall. The performance of SPHERA demonstrates that it can be a valuable resource for improving climate monitoring by providing insights into regional climate change impacts (Giordani et al., 2023).

2.3 Climate model data

The French Centre National de Recherches Météorologiques (CNRM) provides two climate simulations for the period 2000-2018. The first simulation is based on an RCM model, CNRM-ALADIN (Nabat et al., 2020), covering the Med-CORDEX domain, driven by the ERA-Interim (80 km) reanalysis (Dee et al., 2011), while the second one is based on a CPM model, CNRM-AROME, covering the pan-Alpine domain defined within the CORDEX FPS on Convection programme (Lucas-Picher et al., 2023; Coppola et al., 2020). CNRM-ALADIN (hereafter RCM) has a horizontal resolution of 12.5 km and is the limited area version of ARPEGE-Climate. CNRM-AROME (hereafter CPM), is a convection-permitting model dynamically downscaled form CNRM-ALADIN, with a resolution of 2.5 km. CPMs are kilometer-scale regional climate models, with typically horizontal gridding of less than 4 km, which allows a more accurate representation of surface and orographic features. They are also non-hydrostatic models that can explicitly resolve deep convection and therefore better represent convective phenomena, such as heavy convective precipitation. Further information on these climate model simulations can be found in (Caillaud et al., 2021)

2.4 Bioclimatic indices

This study considers ten bioclimatic indices (summarised in Table 1): eight of them, recommended by the International Organisation of Vine and Wine (OIV), are based on temperature and heat accumulation, while the other two are based on rainfall accumulation.

The temperature-based indicators are:

1. Daily mean temperature during vegetation period (TmVeg) calculated between 1st April to 31st October (Jones et al., 2005). Temperature in spring plays a key role in determining the timing of the phenological events, as underlined by Malheiro et al., (2013). In general, higher TmVeg leads to an anticipation of the phenological phases, while TmVeg values above 24 °C or below 12 °C are considered unfavourable to wine-growing (Eccel et al., 2016).

2. Heliothermic Huglin index (HI), which is calculated by summing, when positive, the average between the mean and the maximum temperature, in relation to the baseline temperature of 10°C i.e. the physiological threshold for the start of the vine growth cycle (Huglin M, 1978; Teslić et al., 2018), over the period from 1st April to 30th September and corrected by a coefficient of day duration. The HI index is tied to vine growing and grape sugar concentration with higher HI leading to an increased vine vigour and higher sugar content in the grapes. According to Tonietto and Carbonneau (2004), a climate with a heat index (HI) of more than 3000 degrees per day is classified as 'very warm', while below 1200 degrees per day is “too cold”. Both these situations are associated to plant stress and thus lead to a production reduction.

3. Winkler degree days (WI), which provides a measure of heat accumulation during the growing season, is the sum of daily mean temperatures above 10°C from 1st April to 31st October (Amerine and Winkler, 1944; Piña-Rey et al., 2020). Similarly, to HI, WI index is linked to the rate of growth of the vines and the development of the fruits, with values between 850 and 2700 degree days being optimal for the wine production (Eccel et al., 2016).

4. Biologically Effective Degree Days (BEDD), which is the sum of daily mean temperatures in the range between 10 °C and 19 °C, from 1st April to 31st of October. The BEDD index uses the same baseline temperature (10 °C) as WI and HI indices but also take into consideration that vine growth is unlikely to occur above the upper temperature threshold of 19°C (Anderson et al., 2012; Gladstones, 1992). As the previous temperature-based indices, too high (above 2000 degrees per day) or too low (below 1000 degrees per day) values of BEDD can potentially reduce productivity.

5. Cool Night Index (CNI), defined as the average minimum air temperature during the month of September. Low minimum temperatures in September increase the polyphenolics in the grapes and are beneficial for the overall quality

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of the harvest (Tonietto and Carbonneau, 2004). Although CIN is more related to grape quality than quantity, Massano et al (2023) found that this index can help explaining changes in productivity especially when used in combination with other bioclimatic indices.

6. Minimum temperature during vegetative period (TnVeg), which is the minimum temperature recorded during the vegetative period (1st April to 31st October). This index is important to assess the occurrence of spring frosts that pose a significant risk to viticultural practices and production. The damage threshold is fixed at -2 °C (Sgubin et al., 2018).

7. Maximum temperature during vegetative period (TxVeg), which is the maximum temperature recorded during the vegetative period. This index is useful for assessing the occurrence and the severity of summer hot-spells that can damage to vineyard, thus reducing the wine productivity (Cabré and Nuñez, 2020). The heat stress threshold is set at 35°C, above which physiological damage to the vines is expected (Hunter and Bonnardot, 2011).

8. Minimum temperature during rest period (TnRest), defined as the minimum temperature during rest period, i.e. 1st November to 31st March. This index is used to determine winter severity. Grapevines can tolerate temperatures as -25 °C (Düring, 1997; Lisek, 2012), although damage can already occurs at -15 °C (Eccel et al., 2016)

The indices based on precipitation are:

1. Growing season precipitation index (GSP), defined as rainfall accumulated from 1st April to 30th September and used to assess the water stress for non-irrigated grapevines (Blanco-Ward et al., 2007; Piña-Rey et al., 2020), as in Italy where irrigation is only allowed in extreme cases (e.g. long drought periods).

2. Spring Rain index (SprR), which measures the amount of rain accumulated between the 21st of April and the 21st of June (Raül Marcos-Matamoros et al., 2020). This indicator of spring wetness can be related to production. In fact, while dry springs can delay vegetative growth, wet ones can increase plant vigour but also lead to a higher risk of fungal diseases (Alessandro Dell'Aquila, 2022).

Table 1: Acronyms and formulas of the bioclimatic indices used.

	Definition	Formula	Suitable class range
Temperature-based	Mean temperature during vegetation period (TmVeg)	$TmVeg = T_{mean}$ (1) *between 1st April and 31th October*	13-24 °C (Eccel et al., 2016)
	Heliothermic Huglin index (HI)	$HI = K\sum_{01Apr}^{30Sep} max\left[\left(\frac{(T_{mean}-10)+(T_{max}-10)}{2}\right);0\right]$ (2) K=1.04 length of days coefficient	1200-3000 °C (Tonietto and Carbonneau, 2004)
	Winkler degree days (WI)	$WI = \sum_{01Apr}^{31Oct} max\left[\left(\frac{T_{min}+T_{max}}{2} - 10\right);0\right]$ (3)	850-2700 °C (Eccel et al., 2016)
	Biologically Effective Degree Days (BEDD)	$BEDD = \sum_{01Apr}^{31Oct} min\{max\left[\left(\frac{T_{min}+T_{max}}{2} - 10\right);0\right];9\}$ (4)	1000-2000 °C (Gladstones, 1992)
	Cool Night Index (CNI)	$CNI = \frac{1}{30}\sum_{01Sep}^{30Sep} T_{min}$ (5)	12-18 °C (Tonietto and Carbonneau,

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			2004)
	Minimum temperature during vegetative period (TnVeg)	$TnVeg = T_{min}\ between\ 01\ Apr\ and\ 31\ Oct$ (6)	Damage threshold -2 °C (Sgubin et al., 2018)
	Maximum temperature during vegetative period (TxVeg)	$TxVeg = T_{max}\ between\ 01\ Apr\ and\ 31\ Oct$ (7)	Upper threshold 35 °C (Hunter and Bonnardot, 2011)
	Minimum temperature during rest period (TnRest)	$TnRest = T_{min}\ between\ 01\ Nov\ and\ 31\ Mar$ (8)	Above -25 °C (Düring, 1997; Lisek, 2012)
Precipitation-based	Growing season precipitation index (GSP)	$GSP = \sum_{01Apr}^{30Sep} Prec$ (9) *Prec: total precipitation*	200-600 mm (Badr et al., 2018)
	Spring Rain index (SprR)	$SprR = \sum_{21Apr}^{21Jun} Prec$ (10)	(Dell'Aquila, 2022)

2.5 Validation of climate simulations and calculation of bioclimatic indices

In this work, temperature and precipitation data from the observational dataset E-OBS, the climate reanalysis product SPHERA and the climate model simulations, at regional (RCM) and convection-permitting scale (CPM), are used for the calculation of the above-described bioclimatic indices. The analysis focuses on the 19 years from 2000 to 2018 that is the longest period available for RCM and CPM simulations and in common with E-OBS, SPHERA as well as FRA and MON productivity data.

To compare the observational datasets and climate simulations among each other (Berg et al., 2013), they are first all remapped on a common grid, i.e. E-OBS regular grid, at ~11 km. Tests performed to investigate the effects of the remapping strategy on the climate variables showed that the results are not impacted by the resolution chosen for the remapping (not shown).

Then, the climatic variables (i.e. P: Precipitation; TM: mean temperature, TX: max temperature and TN: min temperature) are retained on all available grid cells within the areas of interest (LOM and TOS). Subsequently, the consortium territory is cropped using the respective shape files of FRA and MON. Finally, the spatial average is calculated by weighing the contribution of each grid cell according to the percentage of the cell falling within the consortium territory. The shape file of the FRA consortium's territory is provided directly by the consortium's technical office, while the shape file for MON is created by selecting the municipality listed in the appellation regulation for the relevant denominations (i.e., Montepulciano municipality). The same methodology is used to calculate the bioclimatic indices.

The precipitation and temperature time series of the climate simulations are analysed against the observational datasets to evaluate the biases in the climatic conditions in the region of interest, prior to examine the bioclimatic indices. In

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particular, the CPM performance is evaluated for the common period 2000-2018 against both SPHERA and E-OBS and compared to the RCM. In this study, the new SPHERA reanalysis product is used as a reference dataset together with the E-OBS dataset, which is already widely used for model validation (Kyselý and Plavcová, 2010). SPHERA and E-OBS time series together provide a range within which the CPM and the RCM time series are expected to fall, similar to a 'confidence interval'.

The comparison between SPHERA (E-OBS) and CPM, as well as SPHERA (E-OBS) and RCM, is carried out by computing the Spearman correlation and RSME, the percentage differences of RMSE with the mean of the reference (SPHERA and E-OBS) (RMSE%) is also indicated for the cumulable variables (i.e. BEDD, HI, WI,GSP, SprR and precipitation). This allows to analyse whether the variability of SPHERA and E-OBS data is reproduced by CPM and RCM simulations and asses the biases between model simulations and both reanalysis and observations. Statistical significance of the differences between model simulations and both reanalysis and observations is assessed by a Welch's two-tailed t-test, with a 95% level of confidence.

Finally, a trend analysis for both the climatic variables and the bioclimatic indices is performed to assess the evolution of the climatic condition in FRA and MON in the period 2000-2018; the same analysis is also carried out for productivity data. The non-parametric Mann-Kendall test and the Sen's slope estimator are used to determine the presence and the magnitude of trends with a significance level of 95% (Hanif et al., 2022; Mann, 1945). The assessment of possible trends aims to investigate whether the long-term component of variability may be dominant over the interannual component.

2.6 Single and multi-regression approach

The Spearman correlation coefficient between each bioclimatic index and wine grape productivity is calculated for both consortia area and the threshold for statistical significance is set to 95%. This analysis aims at assessing the fraction of wine grape productivity variability explained by the bioclimatic indices and the ability of climate models to represent this relationship compared to the observational datasets.

Furthermore, a multi-regressive (MR) approach is applied to determine whether a linear combination of indices can enhance the total productivity variability explained by the bioclimatic indices (Massano et al., 2023). The best subsets regression technique is used to establish the most suitable combination of indices. This approach seeks the predictor subset of bioclimatic indices that most accurately predicts the outcome variable, i.e. the productivity. It examines all feasible predictor combinations and removes irrelevant ones to streamline the model. The k-fold cross validation method is employed to identify the optimal model (Kassambara, 2017). This method performs cross-validation by randomly dividing the data into k subsets (k-fold) approximately of equal size, with k typically set to 5 or 10 (here k = 5 is used). One of the folds serves as test set and the remaining as training. This process is repeated k times, whereby varying groups of data are utilized as training or testing sets. Subsequently, the mean squared error is computed. The average of the mean squared errors of all iterations is the model prediction error (CV - cross validation error) (James et al., 2021; Kuhn and Johnson, 2013; Wassennan, 2004). The performance of the multi regressive model is assessed

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by the adjusted R-squared coefficient of determination (AdjR^2), while the p-value is used to determine statistical significance at 95% level. The so optimised multi-regression model is then used to predict the past productivity, which is compared to the observed productivity using the Pearson correlation. When the MR method provides statistically significant results, the variance explained by the MR model is compared with the maximum variance explained by SR to determine which method provides the best performances.

3 Results

3.1 Validation of the climate simulations

The precipitation and temperature time series of both CPM and RCM are validated against the observational datasets to evaluate the biases in the climatic conditions of the consortia (FRA and MON), which could lead to biases in the bioclimatic indices. To this end, Figure A 2 for FRA, and Figure A 3 for MON, show the precipitation (P) and temperature (TM: mean temperature, TX: max temperature and TN: min temperature) time series of E-OBS, SPHERA, RCM and CPM for the common period 2000-2018. In MON, E-OBS minimum temperature time series shows a strong decrease of almost 2°C between 2015 and 2018 (Figure A 3), which is not observed in any of the other datasets. Further investigations highlighted that this temperature fall affects the entire TOS and is inconsistent with other observational records (not shown). This E-OBS misrepresentation of the temperature field affects consequentially the mean temperature time series (Figure A 3), the temporal correlations (Table A 2), and is likely to be reflected in the temperature-based indices. Previous studies have shown that E-OBS underestimates monthly and seasonal average temperatures when compared to stations observations (Liakopoulou and Mavromatis, 2023). In general, both RCM and CPM show high and significant temporal correlations with SPHERA for all the climate variables in both consortia (Table A 2), indicating that RCM and CPM reproduce the same variability of SPHERA, although the climate simulations tend to overestimate mean and maximum temperature while underestimating the minimum, as reflected by the statistical differences in mean values (Table A 3). In FRA the variability observed in E-OBS is always reproduced also in RCM and CPM simulations. The Welch's t-test confirmed that E-OBS is closer in mean value to RCM than CPM simulations. Figure 2 and Figure 3 show the ten bioclimatic indices time series computed in the two consortia areas for E-OBS, SPHERA, RCM and CPM. All the bioclimatic indices show very high and significant temporal correlation between SPHERA and both RCM and CPM in both consortia (Table 2). Similar conclusion can be draw for the comparison of the climate models with E-OBS in FRA, while in MON four temperature-base indices (i.e. BEDD, WI, TnVeg, CNI) are not significantly correlated, likely due to the low correlations in medium and minimum temperature (Table A 2). The correlations, especially with SPHERA, tend to be slightly higher for the CPM than for the RCM for most indices, despite the higher RMSE in the CPM (Table 2). The strong correlation between SPHERA and climate simulations (Table 2) indicates that RCM and CPM reproduce the same variability of SPHERA, despite the statistical differences in mean values (Table A 4). The same conclusion is valid also for the comparison of RCM and CPM to E-OBS. This analysis suggests both CPM and RCM could be a valid alternative to observational datasets to investigate the impact of climate on viticulture, despite the biases affecting the climate simulations.

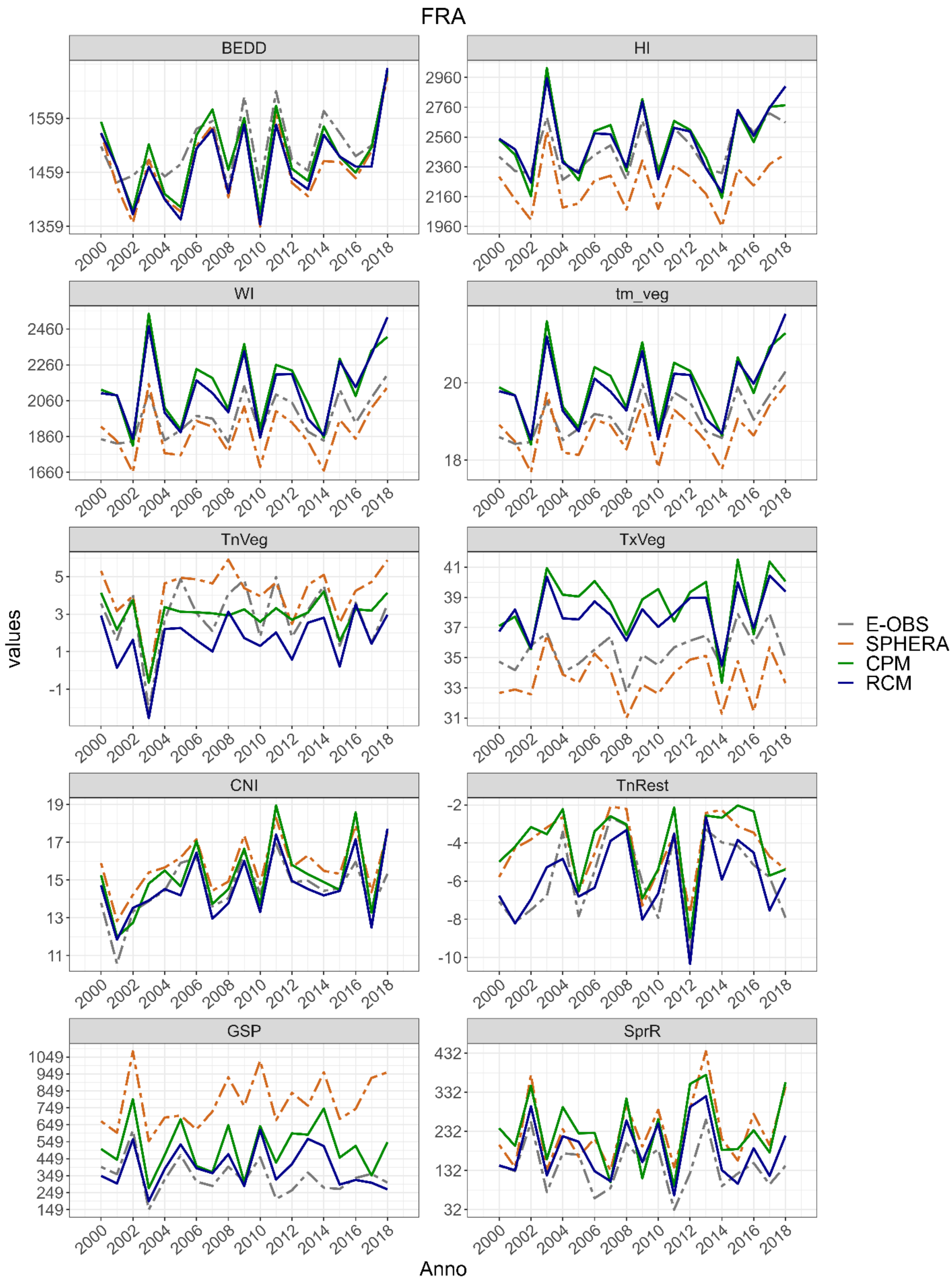

Figure 2: Bioclimatic indices time series 2000-2018, averaged on the FRA consortium area.

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Figure 3 Bioclimatic indices time series 2000-2018, averaged on the MON consortium area.

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In FRA, the correlation coefficients are similar between climate simulations, observations, and reanalysis for the temperature-based indices, while diverge and are not significant for the precipitation-based ones (Figure 4). Few cases are statistically significant: CNI with model simulations, SPHERA, and E-OBS; the BEDD index only when RCM and E-OBS are used. In these cases, the long-term component of the total variability may be dominant, since BEDD, CNI, as well as the FRA productivity, have significant trends (Table A 5). RCM presents a statistically significant outcome also for TnRest, which does not show trend over the period 2000-2018. In this case, the interannual variability might be more relevant to explain productivity. The statistically significant coefficients are all positive indicating a positive effect on productivity of BEDD, CNI and TnRest.

In a previous study, conducted at regional scale using ISTAT productivity data and E-OBS (v26), Massano et al. (2023) did not find any statistically significant correlations for LOM neither with temperature-based nor precipitation-based indices. This indicates that working at a local scale is crucial to improve the portion of productivity variance explained by the bioclimatic indices, while the use of CPM for FRA does not provide any advantage compared to the RCM. Productivity data show a significant positive trend in FRA (Table A 6)

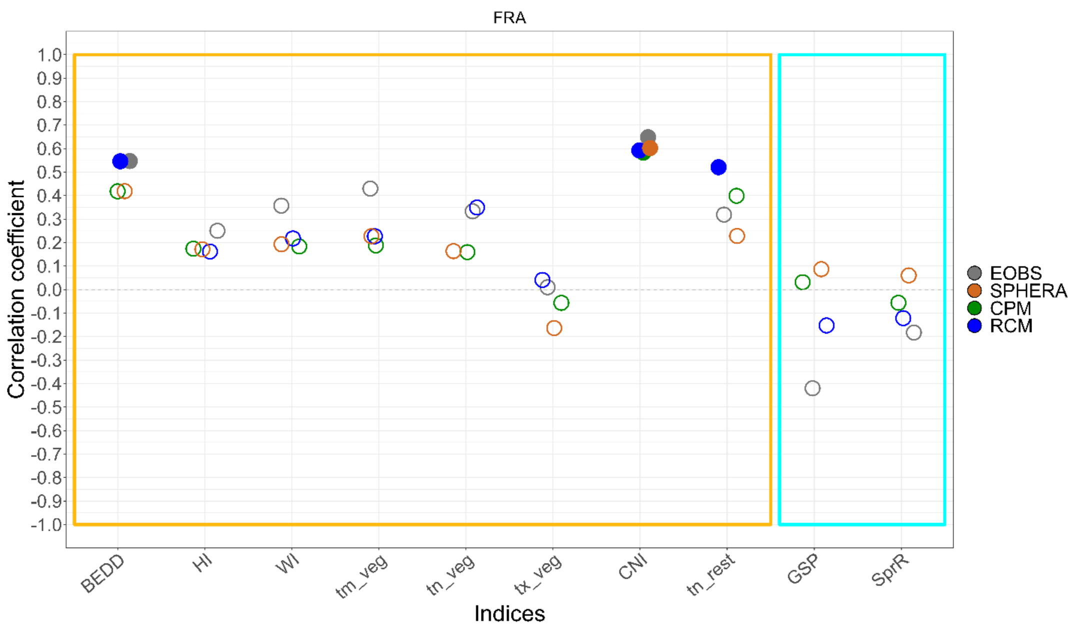

Figure 4: Spearman correlations coefficients between bioclimatic indices and wine grape productivity in FRA. Full coloured circles indicate significant correlations (p<=0.05).

In MON, the correlations between productivity and bioclimatic indices are similar across all the datasets for BEDD, HI, WI and TmVeg but show greater variation for all other temperature-based and the precipitation-based indices (Figure 5). Significant results are found for TnVeg, only using CPM, and for TxVeg in all datasets. We highlight that TxVeg displays a negative correlation, indicating that extreme temperatures during the growing period have a negative impact on production. This aligns with wine makers expectations and is partially supported by results from FRA (Figure 4), despite not being statistically significant. Both TnVeg and TxVeg indices show a significant positive trend

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Table 2: Spearman correlation coefficient the root mean square error (RMSE) of the indices time series and the percentage differences of RMSE with the mean of the reference (SPHERA and E-OBS) (RMSE%) for the cumulative variables. Bold font and asterisk (*) indicate a statistically significant result (p>=0.05)

FRA													
	SPHERA vs CPM			SPHERA vs RCM			E-OBS vs CPM			E-OBS vs RCM			
Index	ρ	RMSE	RMSE%	ρ	RMSE	RMSE%	ρ	RMSE	RMSE%	ρ	RMSE	RMSE%	Index
BEDD (GDD)	**0.97***	26.62	1.8	**0.96***	19.39	1.3	**0.85***	37.29	2.5	**0.91***	45.78	3	BEDD (GDD)
HI (GDD)	**0.98***	305.88	13.7	**0.96***	308.59	13.8	**0.88***	128.56	5.2	**0.87***	117.36	4.7	HI (GDD)
WI (GDD)	**0.99***	264.91	14	**0.98***	247.63	13.1	**0.85***	209.55	10.7	**0.85***	191.23	9.7	WI (GDD)
TmVeg (°C)	**0.99***	1.24	-	**0.98***	1.14	-	**0.85***	0.98	-	**0.84***	0.87	-	TmVeg (°C)
TnVeg (°C)	**0.63***	1.4	-	**0.95***	2.59	-	**0.65***	1	-	**0.72***	1.53	-	TnVeg (°C)
TxVeg (°C)	**0.81***	5.11	-	**0.48***	4.42	-	**0.52***	3.56	-	**0.64***	2.77	-	TxVeg (°C)
CNI (°C)	**0.95***	0.81	-	**0.87***	1.24	-	**0.85***	1.2	-	**0.85***	0.91	-	CNI (°C)
TnRest	**0.81***	0.76	-	**0.85***	1.99	-	**0.75***	2.14	-	**0.8***	1.17	-	TnRest
GSP (mm)	**0.64***	295.39	37.6	**0.74***	410.3	52.3	**0.5***	204.67	59.9	**0.55***	103.91	30.4	GSP (mm)
SprR (mm)	**0.91***	43.28	18.6	**0.77***	65.38	28	**0.68***	111.33	79.2	**0.84***	57.54	40.9	SprR (mm)
MON													
	SPHERA vs CPM			SPHERA vs RCM			E-OBS vs CPM			E-OBS vs RCM			
Index	ρ	RMSE	RMSE%	ρ	RMSE (°C)	RMSE%	ρ	RMSE	RMSE%	ρ	RMSE	RMSE%	Index
BEDD (GDD)	**0.92***	55.33	4	**0.91***	51.04	3.7	0.35	96.32	6.4	0.43	96.27	6.4	BEDD (GDD)
HI (GDD)	**0.86***	232.29	9.9	**0.94***	233.54	10	**0.82***	151.35	6.3	**0.72***	158.76	6.6	HI (GDD)
WI (GDD)	**0.93***	284.54	16.1	**0.93***	284.39	16	**0.45***	217.68	11.2	0.31	224.69	11.6	WI (GDD)
TmVeg (°C)	**0.93***	1.34	-	**0.92***	1.34	-	0.42	1.02	-	0.31	1.05	-	TmVeg (°C)
TnVeg (°C)	**0.69***	0.94	-	**0.77***	1.76	-	**0.67***	1.36	-	**0.62***	1.58	-	TnVeg (°C)
TxVeg (°C)	**0.75***	2.75	-	**0.83***	2.52	-	**0.86***	2.02	-	**0.82***	1.84	-	TxVeg (°C)
CNI (°C)	**0.97***	0.84	-	**0.95***	0.58	-	**0.49***	1.9	-	0.4	1.38	-	CNI (°C)
TnRest	**0.9***	1.43	-	**0.86***	1.09	-	**0.8***	1.94	-	**0.79***	1.58	-	TnRest
GSP (mm)	**0.48***	128.26	39.1	**0.49***	106.85	32.6	**0.71***	136.38	48.3	**0.71***	45.89	16.2	GSP (mm)
SprR (mm)	**0.84***	60.96	49.9	**0.82***	40.48	33.1	**0.75***	68.15	60.7	**0.81***	34.61	30.8	SprR (mm)

3.3 Bioclimatic indices control on wine grape productivity

3.3.1 Single regression analysis

A Spearman correlation analysis is performed to investigate the relation between the different bioclimatic indices and wine grape productivity and consequently determine the amount of total productivity variability (interannual and long-term) explained by these indices.

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(Table A 7), which suggests productivity being more sensitive to the long-term component of variability, at least for CPM. Productivity data do not show any trend in MON (Table A 8).

Only the CPM simulation shows significant correlation for the precipitation-based index GSP. This could be linked to the more realistic representation of the precipitation field (Prein et al., 2015), although positive correlations with GSP are not expected, as an excessively wet season is usually detrimental to production. Thus, it is possible that other factors influence this correlation, such as specific viticultural practices or vintage management (Priori et al., 2019). For example, harvesting immediately after rainfall may result in the collection of larger grapes, thus increasing the productivity. Additionally, specific trimming techniques can improve ventilation between the branches, reducing the risk of mould and fungus, and thus limiting the negative impact of precipitation on the harvest (Evers et al., 2010).

The MON case shows improvements compared to the analysis done with ISTAT data by Massano et al. (2023). In their analysis, TOS did not show any correlation between wine grape productivity and any bioclimatic indices, despite considering a longer time series. Being FRA and MON productivity data from the same population as the ISTAT productivity data (Table A 1 and Figure A 1), these results confirm that the use of the local scale and including a larger variety of bioclimatic indices can enhance the portion of productivity variability explained by the bioclimatic indices considered.

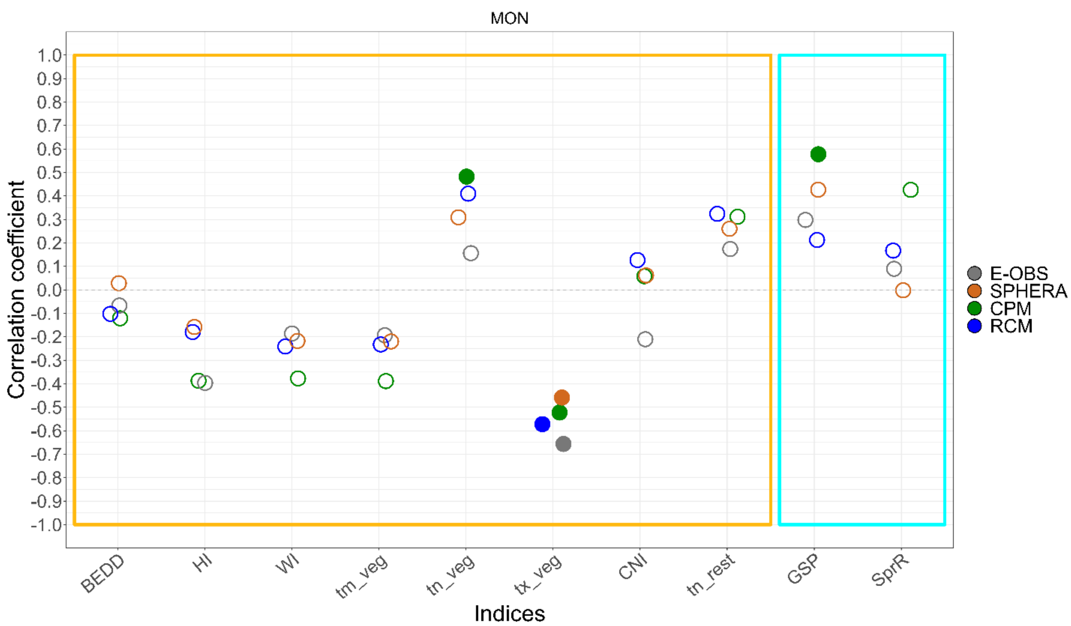

Figure 5: Spearman correlations between bioclimatic indices and wine grape productivity in MON. Full coloured circles indicate significant correlations (p<=0.05).

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3.3.2 Multi-regression analysis

A multi regression (MR) analysis is carried out and compared with the single regression (SR) approach to see if considering a linear combination of bioclimatic indices increases the proportion of productivity variability explained by the indices.

Table 3 shows the results of the MR model, highlighting the selected bioclimatic indices and the variance explained in comparison with the SR method, for each case in both FRA and MON. The authors highlight that, even when the MR selects just one index, this can differ from the single regression due to the correlation method chosen. The MR confirms that the temperature-based bioclimatic indices are more relevant than precipitation-based ones in explaining productivity variability, especially in FRA, where only for RCM the GSP is selected as a predictor. In MON, precipitation-based indices are selected as predictors in the MR model when using the CPM simulation and SPHERA reanalysis, confirming the relative higher importance of precipitation on productivity in this area compared to FRA. Thus, for MON, the improved representation of the precipitation field at convection-permitting scale could be a relevant factor, since in the other cases precipitation-based indices are excluded by the MR.

Table 3: Donuts chart indicating, for E-OBS, SPHERA, CPM and RCM, the best-performing index for the single regression (SR) and the indices included in the multi-regression model (MR), as well as the percentage of variance explained by each model (centre of the donut), in FRA and MON. Orange (blue) colour indicates temperature-based (precipitation-based) indices. The MR Adjusted R2 is expressed in the MR Adj R^2 column.

<table>
<tr><th colspan="4">FRA</th><th colspan="4">MON</th></tr>
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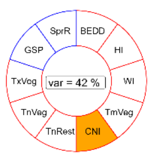
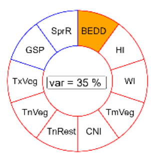
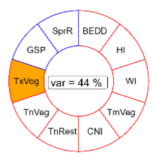
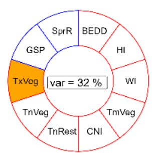
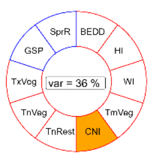
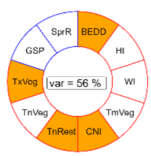
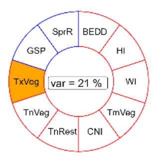
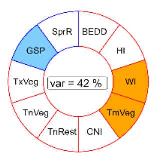
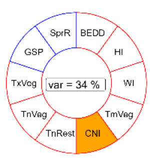
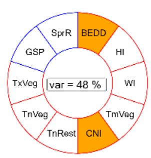
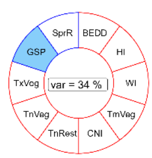
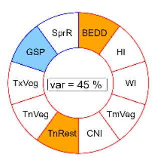
<tr><td>E-OBS</td><td></td><td></td><td>0.31</td><td>E-OBS</td><td></td><td></td><td>0.28</td></tr>
<tr><td>SPHERA</td><td></td><td></td><td>0.43</td><td>SPHERA</td><td></td><td></td><td>0.31</td></tr>
<tr><td>CPM</td><td></td><td></td><td>0.42</td><td>CPM</td><td></td><td></td><td>0.34</td></tr>
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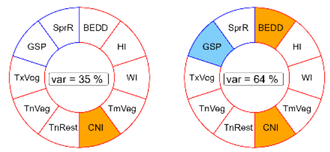
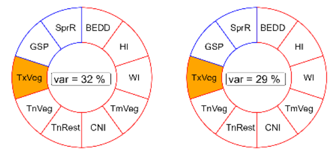
RCM		0.57	**RCM**		0.25

The overview on the performance of the single-regression method (SR) and the multi-regression method (MR) is presented in Figure 6, showing that using a linear combination of bioclimatic indices increases the proportion of explained total productivity variability, especially for FRA.

Overall, the bioclimatic indices explain a higher proportion of productivity variance in FRA compared to MON (Figure 6a and Table A 9), in line with previous findings at regional level for LOM and TOS (Massano et al., 2023). The highest proportion of explained variance in productivity is obtained in FRA with the MR approach and RCM data (64%), followed by SPHERA (56%) and CPM (48%). The variance explained in MON is lower, with a maximum of 45% obtained for CPM and the MR approach, very close to SPHERA with MR (42%) and to E-OBS with SR (44%). The maximum variance in productivity explained by the SR is compared with the MR variance (Figure 6b), demonstrating that the MR better represents productivity variability in FRA in all cases except E-OBS, which shows a slight decrease in performance (-7%). Meanwhile, SPHERA gains 20%, CPM 14% and RCM 29% when MR is compared to SR. In MON, MR provides a better explanation for productivity variance in SPHERA reanalysis and CPM simulation, accounting for an increase of 11% and 21% respectively. However, for the E-OBS dataset and RCM simulation, MR performance decreases slightly (-12% and -3% respectively).

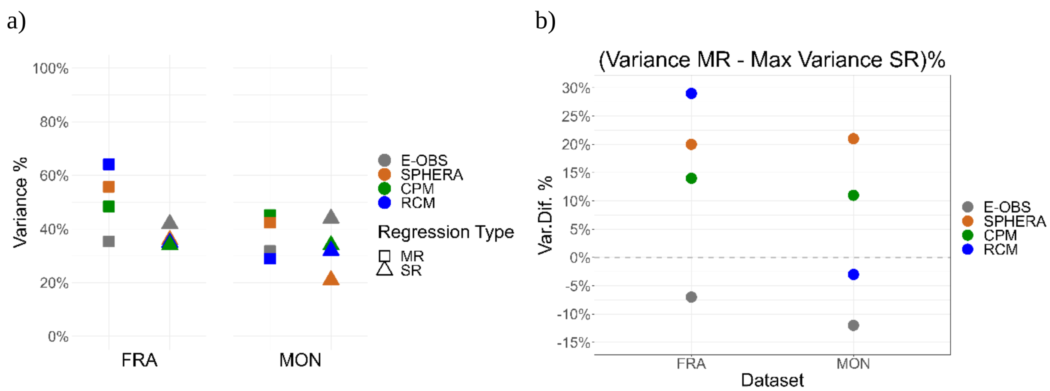


Figure 6: a) The maximum fraction of the wine grape productivity variance (%) explained by SR and MR in each consortium, colours indicate the type of climatic data used, squared (triangular) shape indicates multi regressive (single regressive) approach. b) Variance differences in percentage between MR and SR for FRA and MON.

4 Discussion and conclusion

The study assesses the potential of a CPM to investigate the impact of climate variability on wine grape productivity at a local scale, using bioclimatic indices for the period 2000-2018. The CPM simulation is compared with RCM

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simulation, SPHERA reanalysis, and E-OBS observations. The study uses wine grape productivity data from two Italian wine consortia, namely 'Consorzio per la tutela del Franciacorta' (FRA) and 'Consorzio Del Vino Nobile di Montepulciano' (MON). Single and multiple regression approaches are used to account for the possible interplay of bioclimatic indices in explaining wine grape productivity variability.

Overall, the single regression exhibits high correlation coefficients, but statistically significant results are only found in a small number of cases at the 95% confidence level. The multi-regression method consistently enhances the productivity variability explained by the bioclimatic indices and delivers predictors with potential for usability.

In FRA, the correlation coefficients are exclusively positive, but statistically significant only for temperature-based indices such as BEDD, CNI, and TnRest. There is a high degree of agreement between CPM and SPHERA reanalysis, but E-OBS and RCM presents the highest correlation. Correlations with precipitation-based indices in FRA are not significant and tend to show negative relationships with productivity. These findings suggest that temperature is the main factor affecting production, while precipitation has a negative impact on productivity, potentially resulting in losses due to fungal diseases in the region.

The MON results indicate that only CPM provides statistically significant results for a precipitation-based index (GSP), which is positively correlated with productivity. Also, SPHERA, RCM and E-OBS in this region show positive correlations between precipitation-based indices and productivity, even if they are not significant. This differs from the findings for FRA, where the correlations are negative, even if not significant. However, it is worth noting that there are many differences in the geographical features and types of wine produced in FRA and MON. FRA is in the humid subtropical climatic zone, while MON is situated in the hot summer Mediterranean zone. Other factors, such as vintage management techniques and cultivar selection, can also influence productivity variability in addition to climate, but investigation of these factors is beyond the scope of this paper. Meanwhile, the productivity for both FRA and MON exhibits a negative correlation with TxVeg with all the climatic data considered, but it is only significant for MON. This suggests that extreme maximum temperatures during the vegetative season (1st April - 30th October) may have harmful effects.

These results, which are obtained at a local scale using data from consortia, complement the previous study conducted at regional scale by Massano et al. (2023). The climate models appear to be a useful tool to explain productivity variance using a MR approach, improving the results compared to the E-OBS. However, the use of the CPM does not show a clear added value compared to the RCM since it performs better in MON, but not in FRA. This could be link to the fact that temperature is generally the main driver of wine grape production, and the added value of the CPM may be more evident when precipitation is a dominant factor.

However, the analysis presented here pave the path to the use of climate models to investigate the impact of climate change on wine production in the future. In this context, CPMs can provide new climate information, such as hail risk, which is a convections-related phenomenon that impact grape productivity. Moreover, this work shows an application of the bioclimatic indices to wine grape productivity that is rarely used.

Data availability

Data can be provided by the corresponding authors upon request.

Author contribution

LM, MG and GF Conceptualization and Methodology, LM Formal analysis and Writing – original draft preparation, GF MG and CC Writing – review & editing.

Competing interests

The authors declare that they have no conflict of interest.

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Appendix A

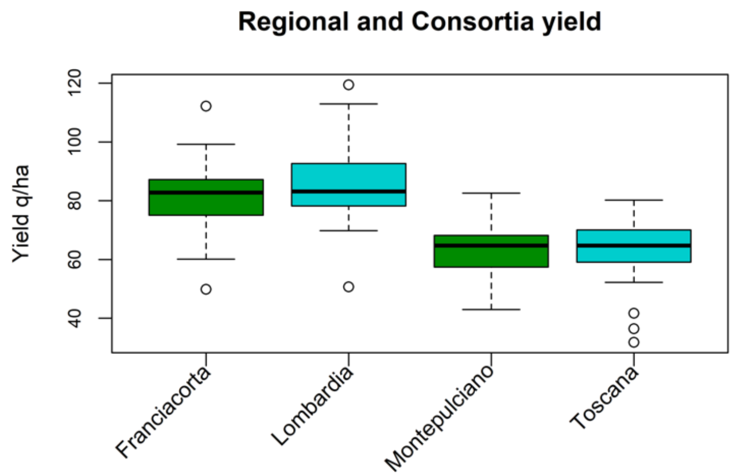

Figure A 1: Boxplot of the regional productivity (cyan) and consortia productivity (green). The series of LOM and TOS come from ISTAT database and cover the period 1980-2019, whit a six-year gap between 2000-2005, the period available for FRA is 1997-2019 (calculated by aggregating the Franciacorta DOCG and Curtefranca DOC denominations) and for MON is 1989-2019 (calculated by aggregating the Vino Nobile and Rosso di Montepulciano denominations), with no gap in the series.

Table A 1: results of Welch's t test (t.stat), the reference value for t.stat (t.tab), the degrees of freedom (DoF) for the t test based on the number of observations computed according to the Welch's equation for effective degrees of freedom (Welch, 1947) and temporal correlation between regional ad consortia productivity data. The * symbol indicates statistically significant results (p<=0.05).

Consortium	*t.stat*	*t.tab*	*DoF*	*Cor.Coef.*
FRA	1.17	2.01	47.94	0.62*
MON	0.1	2	63.99	0.55*

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Figure A 2: Time series of mean (TM), maximum Temperature (TX), minimum (TN) temperature and precipitation (P) over FRA area for the period 2000-2018. All the time series are based on data remapped on E-OBS grid (~ 11 km).

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Figure A 3: Time series of mean (TM), maximum Temperature (TX), minimum (TN) temperature and precipitation (P) over MON area for the period 2000-2018. All the time series are based on data remapped on E-OBS grid (~ 11 km).

Table A 2: Spearman correlation coefficient (ρ) , the root mean squared error (RMSE) between SPHERA (E-OBS) and CPM, as well as SPHERA (E-OBS) and RCM time series and the percentage differences of RMSE with the mean of the reference (SPHERA and E-OBS) (RMSE%). in the FRA and MON area.

FRA									
	TM		TX		TN		P		
	ρ	RMSE (°C)	ρ	RMSE (°C)	ρ	RMSE (°C)	ρ	RMSE (mm)	RMSE%
SPHERA CPM	**0.95***	0.78	**0.94***	1.54	**0.96***	0.39	**0.84***	233.52	18.2
SPHERA vs RCM	**0.95***	0.38	**0.96***	1.73	**0.91***	1.37	**0.73***	415.05	32.4
E-OBS vs CPM	**0.76***	0.64	**0.78***	0.6	**0.55***	0.78	**0.76***	435.99	62.4
E-OBS vs RCM	**0.85***	0.37	**0.82***	0.43	**0.58***	0.61	**0.77***	266.65	38.2
MON									
	TM		TX		TN		P		
	ρ	RSME (°C)	ρ	RSME (°C)	ρ	RSME (°C)	ρ	RSME (mm)	RMSE%
SPHERA CPM	**0.79***	1.06	**0.81***	1.15	**0.78***	0.58	**0.78***	196.26	27.9
SPHERA vs RCM	**0.86***	0.91	**0.92***	1.66	**0.77***	0.77	**0.78***	133.12	18.9
E-OBS vs CPM	0.16	0.79	**0.65***	0.85	-0.08	1.39	**0.86***	177.98	26.2
E-OBS vs RCM	0.06	0.83	**0.52***	0.57	0.04	0.94	**0.8***	128.03	18.8

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Table A 3: Welch's t-test between SPHERA (E-OBS) and CPM, as well as the SPHERA (E-OBS) and RCM time series in the FRA and MON. For each variable (TM, TX, TN and P) the test statistics (t.stat), the t tabulated or critic (t.tab) for a 95% confidence interval and the degree of freedom (Dof) computed using Welch's formula are reported. Bold font and an asterisk (*) indicate the p-value <= 0.05, i.e. the rejection of the null hypothesis (h0) and a statistically significant difference between the mean value of the series.

FRA												
	TM			TX			TN			P		
	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof
SPHERA vs CPM	**4.16***	2.03	35.2	**6.7***	2.03	34.25	**-2.31***	2.03	35.96	**-2.07***	2.03	35.85
SPHERA vs RCM	1.8	2.03	34.77	**7.77***	2.03	34.83	**-8.26***	2.03	35.59	**-4.48***	2.03	35.47
E-OBS vs CPM	**2.98***	2.03	33.1	-1.54	2.03	35.76	**3.84***	2.03	36	**4.93***	2.04	29.22
E-OBS vs RCM	0.5	2.04	32.45	-0.75	2.03	35.95	**-2.24***	2.03	35.83	**2.91***	2.04	32.58
MON												
	TM			TX			TN			P		
	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof
SPHERA vs CPM	**6.45***	2.03	35.57	**5.24***	2.03	35.97	**3.38***	2.04	32.37	**2.33***	2.03	35.69
SPHERA vs RCM	**5.72***	2.03	35.03	**8.15***	2.03	35.83	**-4.8***	2.04	32.12	1.3	2.03	35.91
E-OBS vs CPM	-0.24	2.04	30.12	**-3.29***	2.03	35.99	**4.89***	2.06	24.89	**2.37***	2.03	35.57
E-OBS vs RCM	-0.95	2.04	29.09	-0.81	2.03	35.76	-0.87	2.06	24.71	1.34	2.03	35.96

Table A 4: Welch's t-test between SPHERA (E-OBS) and CPM, as well as the SPHERA (E-OBS) and RCM time series in the FRA and MON. For each bioclimatic index the test statistics (t.stat), the t tabulated or critic (t.tab) for a 95% confidence interval and the degree of freedom (Dof) computed using Welch's formula are reported. Bold font and an asterisk (*) indicate a p-value <= 0.05, i.e. the rejection of the null hypothesis (h0) and a statistically significant difference between the mean value of the series.

FRA													
	SPHERA vs CPM			SPHERA vs RCM			E-OBS vs CPM			E-OBS vs RCM			
Index	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	Index
BEDD (GDD)	-0.92	2.03	35.97	-0.17	2.03	35.97	0.67	2.03	35.36	1.47	2.03	35.35	BEDD (GDD)
HI (GDD)	**-4.50***	2.04	32.50	**-4.71***	2.03	33.34	-0.88	2.04	32.14	-0.96	2.03	33.01	HI (GDD)
WI (GDD)	**-4.48***	2.04	32.68	**-4.13***	2.04	32.65	**-3.25***	2.04	30.29	**-2.89***	2.04	30.26	WI (GDD)
TmVeg (°C)	**-4.59***	2.04	32.60	**-4.17***	2.04	32.59	**-3.28***	2.04	30.54	**-2.85***	2.04	30.53	TmVeg (°C)
TnVeg (°C)	**2.86***	2.03	32.92	**5.35***	2.03	35.87	-0.16	2.04	30.41	**2.42***	2.03	34.63	TnVeg (°C)
TxVeg (°C)	**-8.32***	2.03	32.82	**-8.62***	2.03	35.95	**-5.47***	2.04	30.10	**-5.30***	2.03	34.76	TxVeg (°C)
CNI (°C)	0.99	2.03	33.37	**2.29***	2.03	35.16	-1.22	2.03	33.70	-0.11	2.03	35.37	CNI (°C)
TnRest	-0.23	2.03	35.51	**2.69***	2.03	35.40	**-2.53***	2.03	35.77	0.15	2.03	35.84	TnRest
GSP (mm)	**5.55***	2.03	35.93	**8.76***	2.03	33.94	**-4.23***	2.04	32.17	-1.48	2.03	35.20	GSP (mm)
SprR (mm)	-0.03	2.03	36.00	1.92	2.03	35.18	**-3.80***	2.04	31.84	-1.86	2.03	34.38	SprR (mm)
MON													
	SPHERA vs CPM			SPHERA vs RCM			E-OBS vs CPM			E-OBS vs RCM			
Index	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	t.stat	t.tab	Dof	Index
BEDD	-	2.03	35.88	**-2.13***	2.03	35.84	1.91	2.03	34.16	**2.04***	2.03	34.04	BEDD

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(GDD)	**2.25***												(GDD)
HI (GDD)	**-3.31***	2.03	34.11	**-3.71***	2.03	35.41	-1.37	2.03	33.35	-1.65	2.03	34.90	HI (GDD)
WI (GDD)	**-5.21***	2.03	34.38	**-5.66***	2.03	35.53	**-2.14***	2.03	36.00	**-2.37***	2.03	35.56	WI (GDD)
TmVeg (°C)	**-5.38***	2.03	34.59	**-5.79***	2.03	35.61	**-2.06***	2.03	35.96	**-2.24***	2.03	35.38	TmVeg (°C)
TnVeg (°C)	-0.54	2.03	35.91	**2.90***	2.03	35.78	-1.35	2.03	33.90	1.70	2.03	33.44	TnVeg (°C)
TxVeg (°C)	**-5.43***	2.03	35.98	**-5.36***	2.03	35.06	**-3.74***	2.03	35.86	**-3.57***	2.03	34.60	TxVeg (°C)
CNI (°C)	-1.61	2.03	33.38	0.98	2.03	34.58	**-3.31***	2.03	34.96	-0.92	2.03	35.70	CNI (°C)
TnRest	**-2.27***	2.03	35.17	-0.82	2.03	34.45	**-2.35***	2.03	33.56	-1.01	2.04	32.57	TnRest
GSP (mm)	-1.05	2.04	31.29	**2.46***	2.03	35.02	**-3.06***	2.05	26.93	-0.04	2.03	35.74	GSP (mm)
SprR (mm)	**-2.44***	2.05	27.64	-0.44	2.04	31.33	**-2.75***	2.04	32.09	-0.95	2.03	35.18	SprR (mm)

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Table A 5: Sen's slope FRA, bold font, and asterisk (*) indicate a significant trend (p<=0.05)

FRA	TM (°C/yr)	TX (°C/yr)	TN (°C/yr)	P (mm/yr)	BEDD (GDD/yr)	HI (GDD/yr)	WI (GDD/yr)	TmVeg (°C/yr)	TnVeg (°C/yr)	TxVeg (°C/yr)	CNI (°C/yr)	TnRest (°C/yr)	GSP (mm/yr)	SprR (mm/yr)
E-OBS	**0.05***	0.05	**0.06***	-5.91	**4.59***	**14.96***	11.67	**0.06***	0	0.1	0.09	0.03	-4.77	-1.33
SPHERA	0.04	0.03	**0.04***	12.89	4.5	9.25	6.65	0.04	0.02	0.05	0.1	0.02	**13.32***	**4.57***
CPM	0.04	0.03	0.04	6.54	3.35	13.34	12.61	0.06	0.01	0.12	**0.13***	0.05	-1.31	0.7
RCM	**0.05***	0.04	**0.04***	-2.14	4.19	11.51	11.94	0.06	**0.05***	**0.12***	0.12	0.07	-2.41	-0.15

Table A 6: Sen's slope productivity FRA bold font, and asterisk (*) indicate a significant trend (p<=0.05)

FRA	Productivity (q/ha)/yr
slope	**1.28***

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Table A 7: Sen's slope MON, bold font, and asterisk (*) indicate a significant trend (p<=0.05)

MON	TM (°C/yr)	TX (°C/yr)	TN (°C/yr)	P (mm/yr)	BEDD (GDD/yr)	HI (GDD/yr)	WI (GDD/yr)	TmVeg (°C/yr)	TnVeg (°C/yr)	TxVeg (°C/yr)	CNI (°C/yr)	TnRest (°C/yr)	GSP (mm/yr)	SprR (mm/yr)
E-OBS	**-0.07***	0.04	**-0.11***	8.64	**-7.89***	1.23	**-17.42***	**-0.08***	-0.09	0.07	-0.07	0.03	4.38	0.07
SPHERA	0.03	0.01	**0.03***	**19.47***	2.94	5.05	7.22	0.03	**0.1***	**-0.08***	**0.12***	0	**10.36***	0.99
CPM	0.03	0.02	**0.03***	5.28	2.42	6.84	3.68	0.02	**0.05***	**0.05***	0.15	0	0.74	1
RCM	0.04	0.03	**0.03***	6.28	1.2	10.5	9.31	0.04	**0.06***	0.01	**0.11***	0.06	-0.08	0.34

Table A 8: Sen's slope productivity MON, bold font, and asterisk (*) indicate a significant trend (p<=0.05)

MON	Productivity (q/ha)/yr
slope	0.43

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Table A 9: ranking of the maximum variance (%) explained for each dataset for each consortium, with the indication of type of method used (SR: single regression, MR multi-regression.)

FRA			MON		
Model	var.value %	type	Model	var.value %	type
RCM	64 %	MR	CPM	45 %	MR
SPHERA	56 %	MR	E-OBS	44 %	SR
CPM	48 %	MR	SPHERA	42 %	MR
E-OBS	42 %	SR	CPM	34 %	SR
SPHERA	36 %	SR	RCM	32 %	SR
E-OBS	35 %	MR	E-OBS	32 %	MR
RCM	35 %	SR	RCM	29 %	MR
CPM	34 %	SR	SPHERA	21 %	SR

APPENDIX C. THE USE ECOCLIMATIC INDICES TO INVESTIGATE CLIMATE IMPACT ON WINE GRAPE YIELD AT LOCAL SCALE

Supplementary data

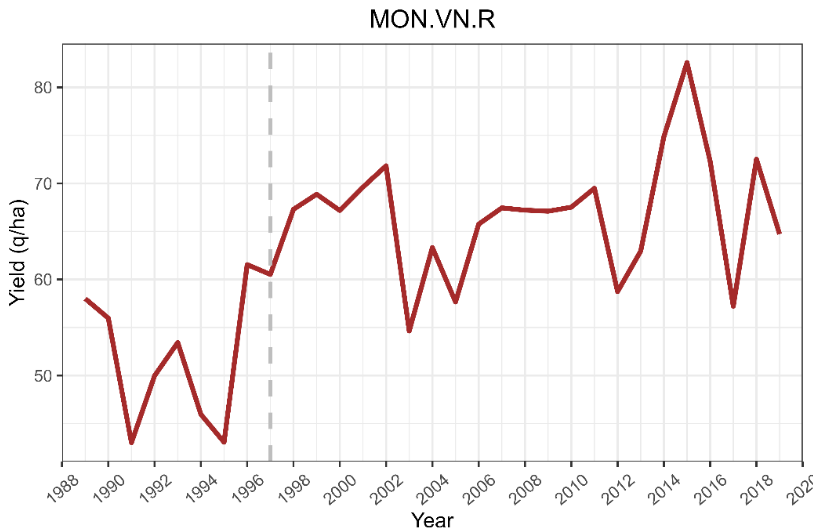

Figure A 4: MON.VN.R yield time series, the vertical dashed line corresponds to the year 1997.

Table A 13: results of the Welch's test to compare the mean values.

t.statistic	p.value	DoF
-5.17	**0.00***	13.10

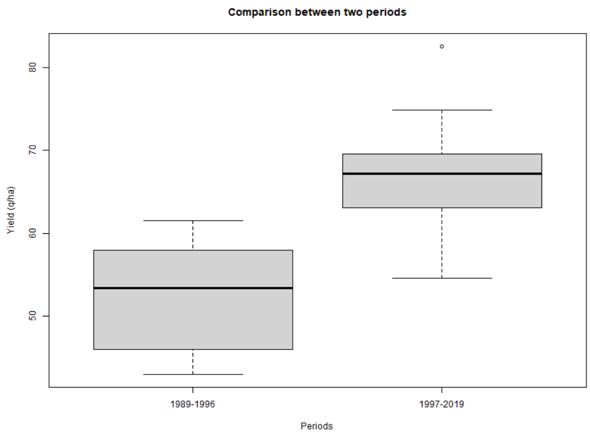

Figure A 5:boxplot of the MON.VN.R time series 1989-1996 and MON.VN.R time series 1997-2019

APPENDIX D. AN EFFICIENCY RELATED FEE FOR CLIMATE SERVICE - VALUATION OF CLIMATE SERVICES FOR VITICULTURISTS: TACKLING FUNGAL DISEASES

Nam, C., Massano, L. T., Graca, A., Cotroneo, R., Dell'Aquila, A., & Caboni, F. (2024). Valuation of Climate Services for Viticulturists: Tackling fungal diseases. Climate Services, 34, 100456. https://doi.org/10.1016/j.cliser.2024.100456 (Nam et al., 2024)

Author Contributions

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Original research article

Valuation of Climate Services for Viticulturists: Tackling fungal diseases

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ABSTRACT

Viticulturists developing adaptation strategies to mitigate the impact of climate change, which affects a grapevine's physiology and wine typicity, can benefit from climate services. Climate services translate physically based variables, such as temperature and precipitation, into actionable, decision relevant bioclimatic indicators, such as Spring Rain, Heat Stress Days, and Warm Spell Duration. These bioclimatic indicators enable the mitigation of fungal diseases, specifically downy and powdery mildew, as well as sunburn. Accurate seasonal forecasts of these bioclimatic indicators can help farmers with viticulture, labor, and stock management, as well as improve the yield and value of wine-quality grapes. Seasonal forecasts of these indicators are available on the MED-GOLD project's dashboard. This study determines an annual service fee to access these forecasts on the dashboard. The annual fee accounts for the seasonal forecast accuracy over part of the Douro wine region of Portugal, as well as the potential savings and losses of micro (⩽1 ha) holding grape growers. The revenue generated from this climate service fee exceeds the cost of dashboard maintenance by nearly 10 times, even with a fee which is less than half of the potential savings of the micro holding farmer.

1. Practical Implications

Seasonal forecasts and climate projections have the potential to help farmers anticipate upcoming needs and devise plans for a more resilient, sustainable, and efficient future (Buontempo et al., 2020; Born et al., 2021; Wiréhn, 2024; Vaughan et al., 2019). Traditionally, these forecasts and projections included only essential climate variables, such as temperature and precipitation. The forecasts and projections did not include relevant bioclimatic variables, such as Spring Rain, Heat Stress Days, and Warm Spell Duration, which are needed to make agricultural decisions. This problem was compounded by the fact seasonal forecasts and climate projections are not easily accessible - both in terms of understanding and use for farmers.

To tackle these problems, the European Union funded the MED-GOLD project (https://www.med-gold.eu/) through its Horizon 2020 research and innovation programme. The MED-GOLD project ran from December 2017 until May 2022. As part of the MED-GOLD project, a simple-to-understand and easy-to-use dashboard (https://dashboard.med-gold.eu/) was created. The MED-GOLD Dashboard covers three time periods: the historical climate (1979–2020), seasonal climate forecasts (1993–2021), and long-term climate projections (2031–2060; 2071–2100) (Dell'Aquila et al., 2023). The MED-GOLD Dashboard provides essential climate variables, as well as bioclimatic indicators, for three key agricultural sectors of the Mediterranean, namely grapes, olives, and durum wheat. For each sector, an industrial partner was found to co-design, co-develop, test, and assess the added value of the MED-GOLD proof-of-concept agricultural climate service.

In the grape sector, the industrial partner was SOGRAPE Vinhos (Dell'Aquila et al., 2023), the largest wine company of Portugal. They manage over 1,600 ha of vineyards and produce wines across 5 countries and 3 continents. Fungal diseases and sunburn cause considerable losses in grape yield (20–30 %) and value (20 %) in the single harvest each year (Graça, 2021). Through the co-development of process with SOGRAPE Vinhos (Chou et al., 2023; First feedback report from users on

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wine pilot service development, 2023; Dell'Aquila et al., 2023), seasonal forecasts of Spring Rain, Heat Stress Days, and Warm Spell Duration, with a minimum accuracy of 70 % compared to observations, were identified as being helpful for explaining incidences of fungal diseases and sunburn, while improving viticulture, labor and stock management for grape growers in the Douro Valley (Northern Portugal).

In this work, we have determined an appropriate annual fee to access the seasonal forecast of these three bioclimatic indicators on the MED-GOLD dashboard. To determine the fee, we first calculated the seasonal forecast performance of these three indicators over the Douro Valley wine region. The seasonal forecast performance accounts for the hit-rate, false-alarm rate, and accuracy of the European Centre for Medium Range Weather Forecasts (ECMWF) seasonal forecasts version 5 data (Stockdale et al., 2018; Johnson et al., 2019), known as SEAS5, compared to the ECMWF reanalysis version 5, known as ERA5, of historical weather and climate data Hersbach et al. (2020); Bell et al. (2021). The second component of determining the annual fee, includes a cost-benefit analysis identifying the potential savings and losses of a micro holding grape grower. Micro holding grape growers make up the vast majority of grape growers in Douro Valley wine region, making their perspective essential when determining a climate service fee. Combining the results of both analyses, a range of "access fees" was proposed according to the accuracy of the seasonal forecast.

The results showed the SEAS5 seasonal forecasts of the three bioclimatic indicators starting in March to be 54–60 % accurate, compared to the ERA5 reanalysis, for hotter- and/or wetter-than-normal conditions over the Douro region. These forecast accuracies are statistically better than assuming the upcoming season will be "normal", although lower than preferred. Nonetheless, this climate service adds value to the traditional agri-food system.

If the seasonal forecast accuracy is 100 %, incorporating it into the decision making process could save farmers more than 10 % of annual harvest earnings in an average year and more than 15 % in a hotter- and/or wetter-than-normal year. Potential losses due to false alarms, however, must be accounted for.

We propose an annual climate service fee of €20/year to access the seasonal forecasts, over the Douro region, starting in March. This fee was determined by considering: (i) the financial loss due to fungal diseases and sunburn,; (ii) the maximum potential savings of a seasonal forecast in terms of labor and fungicide; and (iii) the 50 % accuracy of the seasonal forecasts starting in March.

In addition, we have shown that the potential revenue that could be generated from the MED-GOLD dashboard seasonal forecast alone, by charging the (minimal) access fee, is almost 10 times the annual maintenance cost of the dashboard. Thus, the revenue could cover adaptive and preventive maintenance activities to improve the MED-GOLD dashboard according to user feedback.

Lastly, the approach developed in this work, to determine the MED-GOLD Dashboard access fee, showed how improvements to the seasonal forecast accuracy directly impact the value of the climate service. The approach we used to identify the value of the climate service tackling fungal disease and sunburn can be applied to other MED-GOLD sector products and climate services. For example, those related to the olive or wheat sectors or future climate projections.

2. Introduction

2.1. MED-GOLD project

The MED-GOLD project was a proof-of-concept agricultural climate service which focused on three staples of the Mediterranean food system: grapes, olives, and durum wheat. Scientific and industrial experts partnered together to demonstrate the added-value of co-designing and co-developing information-driven responses to climate changes. A comprehensive description of the co-development of the MED-GOLD pilot climate service for the grape/wine sector is described in Dell'Aquila et al. (2023).

The agricultural climate service for the wine sector was co-developed with SOGRAPE Vinhos, the largest producing wine company in Portugal. SOGRAPE's participation as a co-designer in this pilot climate service acts as a catalyst, accelerating the engagement within the wine sector. Having a single dedicated "champion user" in the co-production of the climate service tool was particularly important in the Douro wine region (Fig. 1) due to the distribution of grape growers. From the Douro wine region's holding size distribution, shown in Fig. 2, it can be seen that ⩾60 % of grape growers have micro holdings (⩽1 ha). With only one grape harvest per year, the income generated by the harvest on a micro holding is merely supplementary income for the grape grower. Often times, these grape growers can not commit the time needed for the entire process of climate service co-production, which includes repeated interviews, testing and iterating products/services, etc., in addition to their regular jobs. SOGRAPE has the knowledge, resources, and personnel to dedicate to the co-production process with its own full-time Research & Development team. They participate in research projects and disseminate results to grape-growers and the wider wine sector; including the ∼ 1,000 grape growers who sell their products to SOGRAPE (Graça, 2021) in the Douro wine region.

2.2. Douro Wine Region

The Douro wine region is a mountainous region in Northern Portugal (Fig. 3) with a very steep terrain. Tiered terraces have been etched along its steep slopes. The rocky, schistous soil of the Douro region is dry and poor in nutrients, but has excellent heat retaining properties. With terraces offering different variations in altitude, exposures to sun and wind, soil fertility, and atmospheric humidity, the Douro region is a host to a variety of grape types. The six principal red and white grape varieties include, Tinta Amarela, Tinta Barroca, Tinto Cão, Tinta Roriz, Touriga Nacional, Touriga Francesa, Gouveio, Arinto, Malvasia Fina, Rabigato, Viosinho, and Códega.

2.3. Fungal Diseases and sunburn

Some grape varieties, such as Touriga Francesa, which account for approximately 25 % of all grapevines in the Douro wine region (Vinhos e Aguardentes de Portugal, 2020), have tight grape bunches. This makes them more susceptible to fungal diseases, particularly when warm and moist conditions persist and air can not circulate in the grape bunches (Graça, 2021).

Atmospheric humidity in the Douro wine region, in particular after rain in the spring, can drive risk of infection by Plasmopara viticola (downy mildew) (Fig. 4a) (Graça, 2021). When downy mildew emerges during critical phenological stages, such as at blossom or at fruit set, grapes are damaged, ultimately reducing yield. Downy mildew can be avoided by the procurement and application of protection products, such as copper-based formulations. Determining when protection products should be applied relies on daily monitoring of temperature, rainfall, and vegetation conditions. For example, the period after budbreak, when daily average temperature exceeds 10°C and shoots are at least 10 cm long, a rainfall event of 10 mm over 2 days prompts visual inspections for fungal disease development (Graça, 2021). Fungal development in susceptible areas has, historically, appeared one week after the rain event. After a visual verification of fungal development and protection products have been applied, atmospheric humidity conditions must be monitored as ensuing rainfall events may provoke secondary infections. Should this occur, protection products must be reapplied. Protection products may be applied multiple times throughout the growing season (Graça, 2021). Downy mildew protection products, however, have expiration dates over which they lose activity. Their short shelf life means any quantity not used during the growing season should not be carried over.

When high atmospheric humidity conditions are combined with

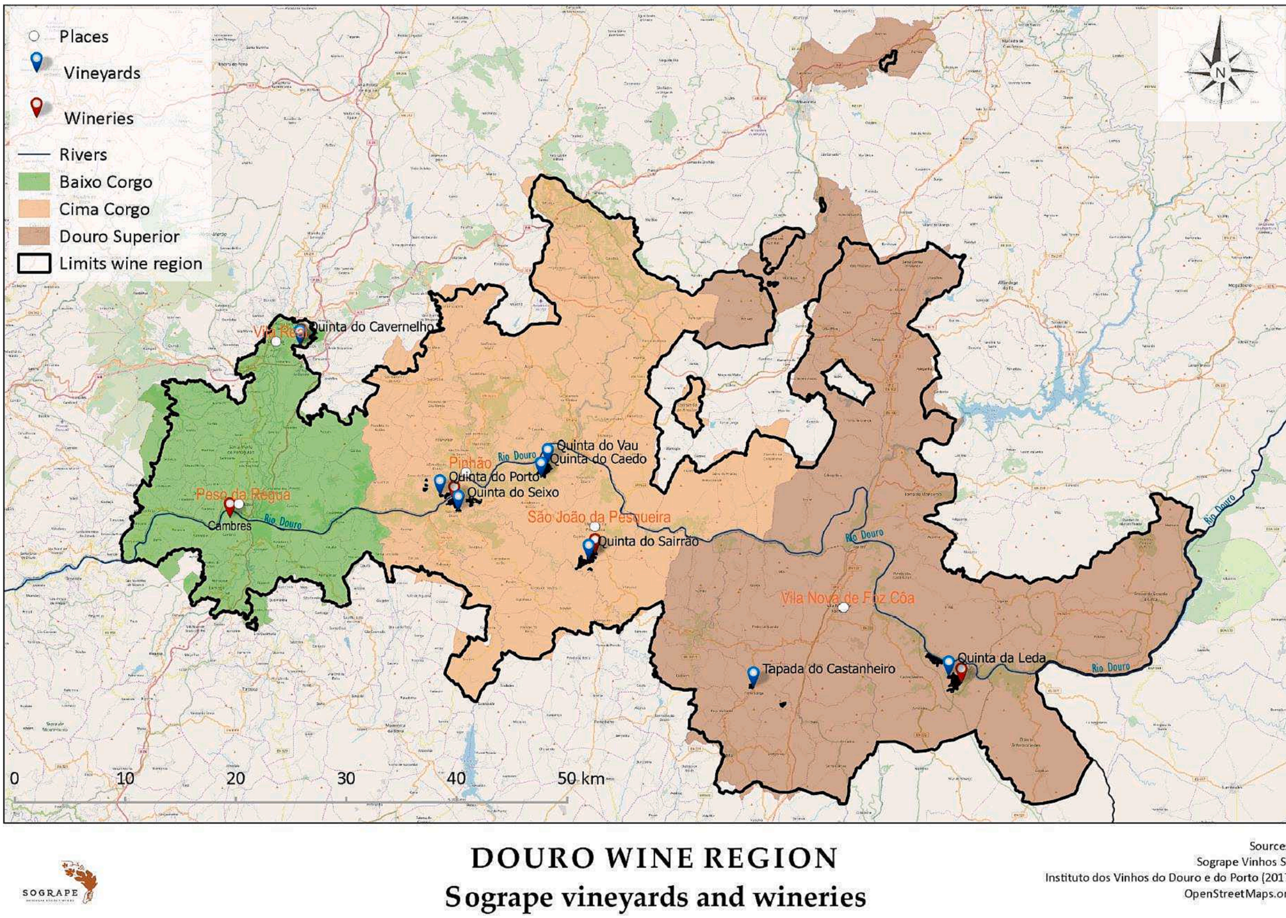

Fig. 1. The Douro Wine Region in Northern Portugal. Image Credit: SOGRAPE (Graça, 2021).

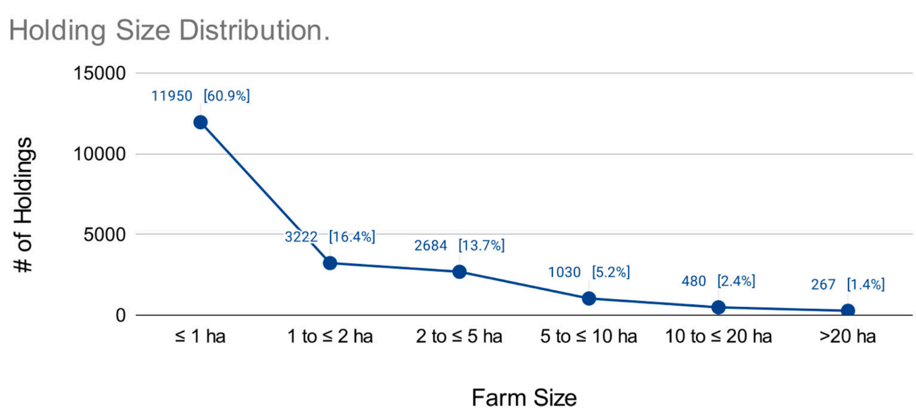

Fig. 2. Distribution of holdings according to Farm Size in the Douro wine region. Percentage of total distribution shown in square brackets. **Data Source:** Instituto dos Vinhos do Douro do Porto, I.P. (2020) (Caracterização et al., 2020).

mild-warm temperatures, sheltered conditions can be created around the bunch zones, especially in high-vigor grapevines. These unaerated bunches may be infected by Erysiphe necator (powdery mildew) (Fig. 4b) (Graça, 2021). Should an infection of powdery mildew occur during the veraison stage of grape bunch development, the result is a loss of grapes quality. Powdery mildew can be avoided through manual trimming and leaf thinning by laborers, known as active canopy management. These exposed grape bunches, however, are susceptible to sunburn as a result of direct solar radiation exposure (Fig. 4c) when temperatures exceed 35°C (Graça, 2021). This is particularly problematic during heatwaves. In addition, when temperatures exceed 35°C, the grapevine undergoes heat stress. The plant closes its stomata and photosynthesis no longer occurs. As the plant uses more water to cool its tissues, it can lead to a disruption in flowering or berry and leaf dehydration, and sunburn. Both sunburn and powdery mildew lead to a decrease in crop quality and value, but active canopy management can prevent the risk of either occurring.

With a single harvest per year, the yield and value of an entire production of wine quality grapes can be significantly reduced, or even lost, due to weather phenomena and viticulture mismanagement. In the Douro region, SOGRAPE found downy mildew typically caused a yield loss of 30 %, whereas sunburn caused a yield loss of 20 %, and powdery

Fig. 3. Mountainous and rocky terrain of the Douro Wine Region. **Photo Credit:** SOGRAPE (Graça, 2021).

(a) Plasmopara viticola, known as Downy Mildew.

(b) Erysiphe necator, known as Powdery Mildew.

(c) Sunburn.

Fig. 4. Examples of (a) Plasmopara viticola, (b) Erysiphe necator, and (c) sunburn. **Photo Credit:** SOGRAPE (Graça, 2023).

mildew caused a value loss of 20 %. These values are the same for all holdings, regardless of size (Graça, 2021).

2.4. Bioclimatic Indicators

Through several workshops, interviews, and focus group discussions with different levels of management, directors, and executives covering SOGRAPE's decision chain in productive and procurement operations the following bioclimatic indicators were identified as being useful for explaining the incidence of fungal diseases and sunburn in grape bunches Chou et al. (2023); First feedback report from users on wine pilot service development (2023); Terrado et al. (2023); Dell'Aquila et al. (2023).

These bioclimatic indicators, for the Northern Hemisphere, are defined as:

1. Spring total precipitation (SprR), the total accumulated rainfall from April 21st to June 21st. This indicator is associated with vigorous undervine growth which increases atmospheric humidity and restricts airflow, contributing to fungal disease risk Dell'Aquila et al. (2023); AWRI (2023).
2. Heat Stress Days (SU35), the total count of days which the daily maximum temperature exceeded 35°C between 1st April and 31st October Chou et al. (2023). This indicator is associated with the number of days photosynthesis of the plant is limited. After veraison, it can affect the sugar, polyphenol, and aroma precursor concentrations in berries, thereby affecting grape and wine quality Chou et al. (2023).
3. Warm Spell Duration Index (WSDI), total count of days which the daily maximum temperature exceeded the 90th percentile for at least 6 consecutive days between 1st April and 31st October Chou et al. (2023). This indicator is associated with dehydration, flowering disruption, and scalding of berries and leaves Chou et al. (2023).

2.5. Climate Service

The workshops, interviews, and discussions also helped determine that the mitigation of fungal diseases and sunburn in grape bunches impacts several operational areas including: viticulture, labor, and stock management Chou et al. (2023); First feedback report from users on wine pilot service development (2023); Terrado et al. (2023); Dell'Aquila et al. (2023). These areas can benefit from a climate service that helps forecast fungal infection risk and sunburn. Seasonal forecasts of

SprR, SU35, and WSDI, with a minimum accuracy of 70 % compared to observations, were presented in a format which was easy to interpret, understand, and use would suit this purpose Fontes et al. (2016); Chou et al. (2023); First feedback report from users on wine pilot service development (2023); Terrado et al. (2023); Dell'Aquila et al. (2023).

An effective climate service providing forecasts with longer lead times allows viticulture management to improve the timing of vineyard operations such as pruning and canopy management, as well as planning fungal disease treatments. Similarly, labor management benefits from improved identification and anticipation of high-demand labor periods for the application of protective treatments and canopy management. Stock management benefits from a climate service that offers adequate anticipation of seasonal climate trends which allows for the early procurement of downy mildew protection products at a lower cost. Additionally, chemical waste can be reduced when the correct amount of downy mildew protection products are purchased.

A climate service that provides accurate seasonal forecasts allows for the timely procurement of fungicide product and hiring of labor to tackle downy and powdery mildew, as well as sunburn, can reduce losses in grape yield and value. For many viticulturists, a key question is *"How much is a climate service worth?"*

Previous work regarding the climatic service market or the valuation of climate service benefits for adaptation Vaughan et al. (2019), such as in Vogel et al. (2017) and Cortekar et al. (2020), or in improved water management Delpiazzo et al. (2023), have not addressed the issue of access fees. The approach developed in this work to determine an annual climate service access fee, in particular where the fee is linked to the performance of the forecast, is novel.

2.6. Valuation of Climate Service

This work determined an acceptable annual fee to access the seasonal forecasts of SprR, SU35, and WSDI on the MED-GOLD Dashboard (described in Section 3.1). An annual fee for seasonal forecast accuracies of 50 %, 70 %, and 90 % was calculated at the request of SOGRAPE (Graça, 2021). The overall forecast accuracy depends on the hit-rate, false-alarm rate, missed forecasts, and correct rejections (described in Section 4.1). The performance of the seasonal forecast is integral for determining the climate service's "value" because it is directly linked to the hiring of labor, product procurement expenditures, and potential savings for the grape growers.

The existing market for the MED-GOLD Dashboard amongst viticulturists in the Douro wine region is driven by micro holding grape growers. Their profit/loss margins will govern the maximum cost of the climate service. Micro holding grape growers indirectly reflect purchasing power and influence purchasing choices. The cost of the climate service must not exceed the potential loss by fungal infection or sunburn, nor significantly reduce profit margins of the grape grower. To determine a valuation of the MED-GOLD Dashboard, it is essential to understand the potential financial gains and losses of a micro holding grape grower due to fungal disease and sunburn. This will be presented in Section 4.2. In this work, the valuation of climate service was based on: (i) the performance of the seasonal forecasts of SprR, SU35, and WSDI on the MED-GOLD Dashboard (Martins et al., 2021; Dunn et al., 2020); (ii) the cost of inaction of fungal disease; and (iii) the potential savings due to actionable climate knowledge. The aim was to propose a reasonable fee for a climate service tackling fungal diseases and sunburn.

2.7. Technical Considerations & Business Sustainability

In addition, this work determined if the existing market in the Douro wine region, with the proposed fee, can sustain the minimum annual IT infrastructure cost of about €12,000, which was determined during the MED-GOLD project's prototype development.

The MED-GOLD Dashboard and the MED-GOLD ICT (Information and Communication Technologies) platforms it relies upon were designed around a Public Cloud-based infrastructure, namely Amazon Web Services (AWS). The main reason for this fundamental architectural choice resided in one of the defining features of Cloud computing: elasticity. While traditional "on-premises" IT infrastructures usually require large capital expenses in order to acquire, configure, build, and maintain a physical data center, publicly available Cloud platforms allow users to dynamically create, manage, and destroy needed IT resources in an elastic way, only generating operating costs when those resources (e.g.: storage, computing units) are actively used. This way, a Cloud-based application, such as the MED-GOLD Dashboard, can still be viable for small-scale scenarios, and, when designed according to best practices, can easily be scaled up as the need arises. For a more detailed description of the technical considerations about the deployment of the MED-GOLD ICT platform and the Dashboard application, please refer to Caboni et al. (2021).

The expected cost of €12,000 included both the MED-GOLD Dashboard web application's infrastructure itself and the entire data processing pipelines it relies upon: source data fetching from the European Union's Earth Observation Programme Copernicus Climate Change Service (C3S) (https://cds.climate.copernicus.eu/) Climate Data Store (CDS), validation and normalization of scripts, indicators calculations, and storage. It is important to note that this cost should be considered as the bare minimum to sustain the recurring cost of the basic Cloud-based IT infrastructure and wouldn't allow for any enterprise-level maintenance or application-level improvements.

3. Materials and Methods

3.1. MED-GOLD Dashboard

The MED-GOLD Dashboard is user-focused web-based application designed and created to visualise and disseminate relevant climate information for three Mediterranean agricultural sectors. For a comprehensive review of the MED-GOLD Dashboard for the grape and wine sector, please refer to Dell'Aquila et al. (2023). There is also a MED-GOLD dashboard user guide entitled "Deliverable 3.5 A handy easy-to-use manual for stakeholders Wine practitioners of the climate service tool. PART II: the grape/ wine sector." available at https://www.med-gold.eu/documents-deliverables/.

The MED-GOLD dashboard presents climate information provided by the CDS Buontempo et al. (2020); Copernicus Climate Change Service (2021). The CDS provides access to numerous quality checked climate data sets including the ECMWF ERA5 reanalysis of historical weather and climate data Hersbach et al. (2020); Bell et al. (2021), which we used to verify the ECMWF SEAS5 seasonal forecasts of atmospheric and oceanic conditions (Stockdale et al., 2018; Johnson et al., 2019). SEAS5 consists of a 51-member ensemble initialised every month on the first day of the month and integrated for 7 months (Johnson et al., 2019). SEAS5 has a spatial resolution of 0.25 degrees. On the MED-GOLD Dashboard, the SEAS5 was used to compute SprR, SU35 and WSDI starting at different months (March to June) Doblas-Reyes et al. (2013) Calí Quaglia et al. (2022) Giuntoli et al. (2022). For a comprehensive description of all CDS products used in the MED-GOLD Dashboard, please refer to the project "Deliverable 7.2 Data Management Plan" available at https://www.med-gold.eu/documents-deliverables/.

The MED-GOLD dashboard presents the climate information for each of the three time periods (historical climate, seasonal forecasts, and long-term projections) in their own sections. In each of these sections, the climate information is classified into the following three categories: Climate variables (e.g. precipitation); Bioclimatic indicators (e.g. Spring Rain); and Wine Risk Indicators (e.g. Sanitary and Heat Risk). The dashboard is a visualization focused web-based application that also allows users to browse, view, and download climate data. Relevant parameters can be selected one-by-one according to preferred time range, geographic location, scenario type/forecast starting month, climate indicator, etc. The indicators are available in several different formats and visualizations, allowing for easy, quick, and seamless integration into critical decision-making. Users can access and interact with relevant climate information without any programming knowledge or the need to manage large climate data files. The main functionalities of the dashboard were based on specific needs highlighted by SOGRAPE.

The study considers only one component of the MED-GOLD dashboard - namely, seasonal forecasts of three bioclimatic indicators.

3.1.1. MED-GOLD Dashboard: Seasonal forecasts

The seasonal forecasts of each bioclimatic index on the MED-GOLD Dashboard is presented in terciles. The terciles indicate: above normal, normal, or below normal, where 'normal' is defined as the range between the 33rd and 66th percentile over the 1993–2020 period from the bioclimatic index derived from the ECWMF ERA5 reanalysis of global weather and climate Hersbach et al. (2020) Bell et al. (2021). 'Above-normal' is defined as greater than the 66th percentile and 'Below-normal' is defined as less than the 33rd percentile (Deliverable3.2, 2023; Deliverable3.3, 2021). The values which lie above the upper tercile or below the lower tercile are commonly considered as anomalies in climate science (ECMWF, 2021; Deliverable3.5, 2023). The presentation of the indicators as above/below normal is a result of the dashboard's co-development process, taking into account user feedback, allowing for a more diverse range of users of climate information ranging from beginners to advanced First feedback report from users on wine pilot service development (2023); Dell'Aquila et al. (2023).

In this study, we have only considered conditions under which grape growers would benefit from fungicide and sunburn prevention, namely hotter- and/or wetter-than-normal conditions, as recommended by SOGRAPE. As such, we analyzed and reported the performance of the three bioclimatic indicators when above-normal conditions were forecasted in SEAS5 compared to ERA5 reanalysis. This study should not be confused with a comprehensive evaluation of the bioclimatic indicator performance seasonal forecast, which would also investigate the causes of deteriorating performances. For an advanced analysis of the seasonal forecasts of the bioclimatic indicators for the wine sector please refer to Chou et al. (2023).

3.2. Performance metrics of Bioclimatic Indicators

The performance of SEAS5 seasonal forecasts of above-normal conditions, from 1993–2020, for each of the three indicators (SprR, SU35 and WSDI) was calculated for the region over the SOGRAPE company vineyards located in the Douro wine region (lon 7° 0' 59" W, lat 41° 1' 20" N). The SEAS5 resolution of 0.25 degrees translates to approximately 21 km by 21 km over this grid box, which covers approximately 441 km^2. The bioclimatic indicators are homogeneous over the grid-box.

The performance of each of the three indicators is based on the hit-rate, false-alarm-rate, and accuracy of the SEAS5 seasonal forecasts compared to the ERA5 reanalysis Mason et al. (2003). The definitions of hit-rate, false-alarm-rate, and accuracy used are as follows (Eqn. (1)–(3)):

$$H = a/(a+c) \tag{1}$$

$$F = b/(b+d) \tag{2}$$

$$A = (a+d)/(a+b+c+d) \tag{3}$$

Where:

- a denotes a Hit. It is the number of times an event was correctly forecasted and occurred.
- b denotes a False-Alarm. It is the number of times an event was forecasted but did not occur.
- c denotes a Miss. It is the number of times an event occurred but it was not forecasted.
- d denotes a Correct-Rejection. It is the number of times an event was not forecasted and did not occur.

The MED-GOLD dashboard provides seasonal forecasts of SprR, SU35 and WSDI starting at different months (March to June) Doblas-Reyes et al. (2013) Calí Quaglia et al. (2022) Giuntoli et al. (2022). The earlier an accurate forecast can be made the better is for the climate service users. For each index, and for each starting month, the three performance metrics (hit-rate, false-alarm-rate ans accuracy) are calculated. The performance of the bioclimatic indicators over the Douro valley gives a complete picture of the quality product the MED-GOLD project provides the grape growers and helps determine the value of the climate service.

For grape growers using seasonal forecasts for planning purposes, both 'false alarms' and 'missed alarms' are problematic. In the case of a false alarm, the seasonal forecast recommends that grape growers purchase product and hire labour to deal with a hotter- and/or wetter- than-normal summer, an investment that is not needed in the end. The grape growers' money would be lost when a False-alarm occurs. In the case of a missed forecast of a hotter- and/or wetter-than-normal summer, no actionable climate knowledge is gained from the seasonal forecast. The grower does not lose additional money through pre-purchase of unnecessary goods and services on the basis of the forecast suggestion. Their expenses, as well as losses in yield and value, in the season, would be the same as without a climate service.

This work determined the value of the actionable climate knowledge that can be gained from seasonal forecasts by considering the amount of money that could be saved by using the climate service, as well as the impact of missed and false alarms. In other words, we conducted an ecosystem service to find the right value of the climate service.

3.3. Ecosystem Services valuation approach

Ecosystem Services (Burkhard et al., 2018) constitute a socio-ecological approach to analyze the relationship among ecosystems, economics, and social systems trying to measure and quantify the economic impact due to ecosystem changes. According to the Common International Classification of Ecosystem Services (CICES v.5.1 (Haines-Young and Potschin-Young, 2018)) classification, in agricultural fields, ecosystem services related to fungal diseases are included in regulating services: to control, prevent, and reduce the number of fungal disease event.

To find the correct value of a climate service for viticulturists tackling fungal disease and sunburn in the Douro wine region, we took two ecosystem service approaches: 'Market Value' and 'Standard Output'. The approaches are described below. The market value approach is included to provide farmers in the Douro region a relatable analysis, while the standard output approach allows for a generalization of this study to other farmers in the European market.

3.3.1. Market Value

The Market Value approach took into account the average yield, yield loss, and price of good quality grapes, over a six year period from 2014 to 2019, from a >20 ha property in the Douro wine region (Graça, 2021). These values were provided by SOGRAPE and assumed to be representative for the region. The value of €3,136/ha was set as the economic value of ecosystem services based on an average yield of 3,200 kg/ha with an average price of €0.98/kg for a good quality yield of wine grapes (Graça, 2021). We used these values to estimate cost of inaction against fungal diseases and sunburn by vineyard area.

3.3.2. Standard Output

In addition to the market value approach, we also present a valuation based on the European Union's standard output. The Standard Output (SO) of an agricultural crop is defined as the average monetary value of the agricultural output at farm-gate price, in €/ha (Glossary, 2023). The

European Standard Output values are released by EuroStat every few years, which represents the 5-year average of an agricultural product (crop or livestock)(Glossary, 2023). According to Eurostat SO 2013 (EuroStat, 2021) the Standard Output of "Vineyards - Quality Wine" is €2,610/ha for the Norte region of Portugal where the Douro wine region sits. This value was used in the following calculations of inaction. The standard output is used as a classification of agricultural holdings by type of farming and by economic size across Europe (Glossary, 2023). This value was determined by using the average prices from 2011 to 2015 and applied to the 2016 Farm structure survey data (EuroStat, 2021). The standard output includes sales, redeployment, self-consumption and changes in the stock of products, without the costs of transport and marketing, except for those products for which the price for packaging is also included. The standard output does not include direct payments, Value Added Tax (VAT) or taxes on products (European Commission Regulation 1242/2008, European Commission Regulation 1166/2000).

3.4. Farm Personas

The valuation of a climate service which forecasts infections risk, allowing for better hiring practices and the deployment of preventative measures, was performed for 3 personas: the 'Reactive Farmer', the 'Prepared Farmer', and the 'Pro-active Farmer'. The 'Reactive Farmer' makes spontaneous decisions according to present conditions; and is most similar to the 'real world' grape grower who must react in terms of purchasing fungicide and hiring labor as the situation unfolds. The Reactive Farmer is most susceptible to abrupt increases in costs. The 'Prepared Farmer' uses industry knowledge and experience to prepare for infections and procures some fungicide products ahead of time at a lower cost. This persona has the ability to absorb some loss if labor or products are not needed. Lastly, the 'Pro-active Farmer' bases their decision to procure fungicide or hire labor entirely on the seasonal forecast. They assume the seasonal forecast is correct all the time (a.k.a. a 100 % accuracy).

A cost-benefit evaluation was performed for each of these personas for differing seasonal forecast accuracies of the bioclimatic indicators. Tables 1.

4. Results

4.1. Performance of the bioclimatic indicators

The performance of the three bioclimatic indicators from SEAS5 seasonal forecasts, starting at different months, was compared to the ERA5 reanalysis over the SOGRAPE company vineyards. The hit-rate, false-alarm-rate, and accuracy of SprR, SU35, and WSDI are presented in Tables 2–4 respectively. The metrics in Tables 2–4 range from 0 to 100 %. A forecast with a hit-rate lower than 33 % is equivalent to the climatological average range (i.e. within the "normal" range) and as such does not provide actionable climate knowledge to the grape grower. The higher the hit-rate, the better. In regards to the false-alarm rate, a good forecast will have low values. For the accuracy metric, the higher the value, the better.

The hit-rate of seasonal forecasts of SprR starting in March and April are only 25 %, however, as the season progressed the performance improved and the hit-rate of the June forecast rose to 63 %. The false-alarm rates also improved as the season progressed, going from a maximum of 33 % to 11 % in June. The overall accuracy of SprR forecasts for wetter-than-normal springs are all well above 33 % and is better than assuming the climatological mean. The accuracy is good in May and June, above 70 %, however, the forecast starting April is only 54 %.

Table 1
Contingency table.

		Forecasted	
		Yes	No
Observed	Yes	(*a*) Hit	(*c*) Miss
	No	(*b*) False	(*d*) Reject

Table 2
Spring Rain (SprR) performance metrics for seasonal forecasts starting at different months. The hit-rate, false-alarm-rate, and accuracy are shown in percentages (%).

	Mar	Apr	May	Jun
Hit-Rate	25	25	38	63
False-alarm Rate	24	33	11	11
Accuracy	60	54	73	81

Table 3
Number of Heat Stress Days (SU35) performance metrics for seasonal forecasts starting at different months. Values are shown in percentages (%).

	Mar	Apr	May	Jun
Hit-Rate	50	40	30	70
False-alarm Rate	44	31	44	33
Accuracy	54	58	46	68

Table 4
Warm Spell Duration Index (WSDI) performance metrics for seasonal forecasts starting at different months. Values are shown in percentages (%).

	Mar	Apr	May	Jun
Hit-Rate	42	42	58	50
False-alarm Rate	36	50	43	14
Accuracy	54	46	58	69

For SU35 the hit-rate for seasonal forecasts were better in March and June compared to April and May. The June forecast had the best hit-rate with 70 %. Comparably, May forecasts only had a hit-rate of 30 %. The false-alarm rate in both March and May were above 40 %, which is high. The overall forecast accuracies of SU35 for warmer-than-normal conditions, for all starting months, were above 46 % and better than assuming the climatological mean. The best performance accuracy was in June with 68 %.

The hit-rates of seasonal forecasts of WSDI, for all starting months, range from 42 % to 58 %. The false-alarm rate from March through May are quite high, with the April forecast reaching a peak of 50 %. Significant improvements are seen in June (14 %). The overall forecast accuracies of WSDI for hotter-than-normal conditions, regardless of starting month are greater than 46 % for the Douro region and can be considered better than assuming the climatological mean.

Of the three bioclimatic indicators, the most accurate was SprR. The accuracy of SU35 and WSDI, overall, were nearly identical. Interestingly, the hit-rates of SU35 and WSDI were better than SprR, however, their false-alarm rates were worse.

For all indicators, the accuracy of the seasonal forecasts for hotter-and/or wetter-than-normal conditions were most accurate when starting in June. The relatively poorer performance in April and May, compared to March and June could be related to seasonal predictability and to large-scale phenomena influencing the local scale meteorology in spring Broennimann (2007); Giuntoli et al. (2022); Calí Quaglia et al. (2022).

It should be iterated that this study simply reports the accuracy of the seasonal forecast over the SOGRAPE vineyards for the purpose of determining the value of the climate service. This study is not a verification analysis of the seasonal forecasts in general, nor have we investigated the causes of deteriorating performances of the bioclimatic indicators, as found in April. This has been done in the following works of Chou et al. (2023); Dell'Aquila et al. (2023); Stockdale et al. (2018); Johnson et al. (2019).

4.2. Valuation of Climate Service

As mentioned, the cost of the climate service must not exceed the potential loss by fungal infection or sunburn, nor significantly reduce profit margins of a micro holding grape grower. As such, we first determined the cost of inaction against fungal disease. Secondly, we determined the maximum potential savings the seasonal forecasts knowledge can provide. Thirdly, the total cost of the climate service was calculated, which accounts for forecast errors. Lastly, we calculate whether the proposed climate fee can sustain the MED-GOLD dashboard.

4.2.1. Cost of inaction against Fungal Disease

In Table 5 the average yield and income for different holding sizes, based on the market value approach, are presented alongside potential cost of inaction due to fungal disease and sunburn. Additionally, the yield loss, according to Eurostat methodology, in terms of standard output prices of good quality grapes was also calculated (Table 6). We only considered the value of quality grapes necessary for wine in this study and have not considered lower quality grapes.

The potential losses presented for the 1 ha holdings range from €627–941 following the market value approach, and €522–783 following the standard output approach. These potential losses are the upper bound of any climate service fee.

4.2.2. Value of actionable knowledge for Fungal Disease and Sunburn

The next step in the approach developed to determine the value of a climate service for fungal mitigation was to calculate the potential savings a seasonal forecast could provide in terms of early procurement of fungicide and labor. For this we considered the costs associated with an average year (Table 7) and a hotter- and/or wetter-than-normal year (Table 8). The values used in the following section for labor costs, the number of sprays of downy mildew protection product, amount of protection product needed, and costs of protection product, were based on those from a holding in the Douro region averaged over a six-year period (Graça, 2021). On average 9.4 kg/ha of downy product was used per spray, which cost €9/kg when procured 6 months ahead of time, or €16/kg when procured 2 weeks ahead of time (Graça, 2021). For each hectare of the holding, the Pro-Active Farmer could save an additional €110 in labor (Graça, 2021) for an accurate seasonal forecast.

In the cost-benefit analysis presented in Tables 7 and 8, we assume the Reactive Farmer has to procure all downy mildew protection product 2 weeks ahead of time at a higher cost. The Prepared Farmer has purchased the quantity need for 2 sprays 6 months in advance at a lower price. They must make any additional purchases of protection product needed in the season at a higher price. The Pro-active Farmer assumes the seasonal forecast has a 100 % accuracy and purchases all protection product 6 months in advance. The savings relative to the Reactive Farmer is presented for both the Prepared and Pro-Active Farmer.

The results in Table 7 show that a Pro-Active farmer can benefit from a climate service on an 'average' year relative to both the Reactive and Prepared Farmers. For a seasonal forecast with an accuracy of 100 % the Pro-Active farmer could save €373.20, compared to the Reactive farmer, which is more than 10 % of the market value and standard output earned for quality wine grapes on 1 ha. The Pro-Active farmer saves >2.8 times the amount the Prepared farmer saves. Table 8 shows that the Pro-Active farmer aims to gain much more in wet years, through early procurement, if the seasonal forecast is correct. These values show that the Pro-Active farmer could save 16 % of the market value and 19 % of the standard output on a 1 ha farm compared to the Reactive farmer. The Pro-Active farmer saves >3.8 times more than the Prepared farmer saves.

In addition, we computed the savings for a various combinations of prepared and spontaneous downy mildew sprayings (not shown) to determine range of loss/savings due to early procurement of downy mildew products and labor. For 1 ha, assuming 100 % seasonal forecast accuracy, a Pro-active Farmer could save €175 (for 1 spray and labor) to €768 (for 10 sprays and labor) compared to Reactive Farmer in downy mildew product costs. In 2016, 10 sprays were needed; it was the

Table 6
Cost of inaction against fungal diseases for various holding sizes in terms of Eurostat Standard Output 2013 (Euro/ha) for the Norte region of Portugal (EuroStat, 2021).

	1 ha	5 ha	10 ha	160 ha
Vineyards - quality wine	€2,610	€13,050	€26,101	€417,615
Downy Mildew Loss (30% less yield)	€783	€3,915	€7,830	€125,284
Sunburn Loss (20% less yield)	€522	€2,610	€5,220	€83,523
Powdery Mildew Loss (20% value loss)	€522	€2,610	€5,220	€83,523

Table 7
Costs associated with the procurement 4 sprays of downy mildew fungicide, typical of an average year, for a 1 ha holding (Graça, 2021). Savings related to labor included for Pro-Active farmer. Source: SOGRAPE (Graça, 2021).

	# Sprays procured 6 months ahead	# Sprays procured 2 weeks ahead	**Total Costs**	Savings relative to Reactive Farmer
Reactive Farmer	0	4	€601.60	-
Prepared Farmer	2	2	€470.00	€131.60
Pro-Active Farmer (Forecast accuracy 100%)	4	0	€388.40	€373.20

Table 8
Costs associated with the procurement of 6 sprays of downy mildew fungicide, typical of a 'wet' year, for a 1 ha holding (Graça, 2021). Savings related to labor included for Pro-Active farmer. Source: SOGRAPE (Graça, 2021).

	# Sprays procured 6 months ahead	# Sprays procured 2 weeks ahead	**Total Costs**	Savings relative to Reactive Farmer
Reactive Farmer	0	6	€902.40	-
Prepared Farmer	2	4	€770.80	€131.60
Pro-Active Farmer (Forecast accuracy 100%)	6	0	€507.60	€504.80

Table 5
Cost of inaction against fungal diseases for various holding sizes in terms of market value (Graça, 2021). Values rounded to nearest Euro.

	1 ha	5 ha	10 ha	160 ha
Avg. Yield (3,200 kg/ha)	3,200 kg	16,0000 kg	32,000 kg	512,000 kg
Avg. Price for good quality yield (0.98 €/kg)	€3,136	€15,680	€31,360	€501,760
Downy Mildew Loss (30% less yield)	€941	€4,704	€9,408	€150,528
Sunburn Loss (20% less yield)	€627	€3,136	€6,272	€100,352
Powdery Mildew Loss (20% value loss)	€627	€3,136	€6,272	€100,352

Table 9
Costs associated with false-alarm and missed forecasts for labor costs and the procurement of 6 sprays of downy mildew fungicide, typical of a 'wet' year, for a 1 ha holding. Source: SOGRAPE (Graça, 2021).

	# Sprays procured 6 months ahead	# Sprays rightarrow be procured or lost	**Total Costs**	Savings relative to Reactive Farmer
Pro-Active Farmer (Forecast 50% miss)	3	3	€705.00	€197.40
Pro-Active Farmer (Forecast 50% false)	6	-3	€507.60	€−166.40

maximum number of sprays recorded by SOGRAPE (Graça, 2021).

While the savings potential from seasonal forecasts are very attractive, the purpose of Table 9 is to demonstrate the impact of a missed forecast of a hotter- and/or wetter-than-normal year and similarly a false-alarm forecast. When a forecast is missed, the Pro-Active Farmer still saves money relative to the Reactive Farmer. A 'false-alarm' forecasts of a 'wet' year, however, can lead to a loss for the Pro-Active Farmer through wasted protection product and additional labor. The False-alarm rate of seasonal forecasts must be accounted for in the price of the climate service.

4.2.3. Proposed Climate Service Fee

In Table 10 the range of potential savings associated with 1 to 10 sprays are presented for the Pro-Active Farmer compared to the Reactive and Prepared Farmer. This is assuming a seasonal forecast with a 100 % accuracy. Additionally, the average potential savings for 3 to 6 sprays is presented, which is more realistic. This 'averaged potential savings' is what the grape growers aim to gain by using the seasonal forecast of the bioclimatic indicators on the MED-GOLD Dashboard. We used this value to help determine a first estimate of an annual climate service access fee; which we took to be 10 % of the average potential savings for a seasonal forecast with a 100 % accuracy. The choice of 10 % is a very conservative estimate to give us a lower bound of an annual fee. For simplicity, this initial dashboard access fee is scaled linearly by 50 %, 70 %, and 90 % to represent forecast accuracy. This linear relationship can be adjusted if future studies collect and analyse data from more farmers regarding past financial losses due to fungal infection, as well as the financial changes that occur when some farmers incorporate seasonal forecasts into their decision making process.

If using the seasonal forecasts for hotter- and/or wetter-than-normal conditions starting in March, where the accuracy is closer to 50 % rather than 100 % (see Section 4.1), we propose a Climate Service Fee of €20/year. This minimal fee should not act as a barrier for the adoption of the MED-GOLD Dashboard climate service for protection against fungal disease by viticulturists.

While the seasonal forecast accuracy for hotter- and/or wetter-than-normal conditions is best in June, in the context of anticipating hiring labor and the early procurement of fungicides to reduce infection risk, June is too late.

4.2.4. Maintenance and Sustainability of Climate Service for Viticulture

With a proposed Climate Service Fee of approximately €20 per year, which is a low estimate, we determined whether the potential market could sustain the maintenance and sustainability of the MED-GOLD Dashboard. Assuming a market uptake of the Douro holding distributions (Fig. 2), for both 30 % (conservative) and 50 % (realistic, as estimated by SOGRAPE (Graça, 2021)), we show that an annual income of €117,789 and €196,330 can be generated (Table 11).

The calculated annual income far exceeds the expected €12,000/year needed to maintain the MED-GOLD dashboard and accounts for the increased number of dashboard users. This income could cover the costs of continuous monitoring and maintenance of the dashboard's infrastructure; including corrective maintenance (i.e.: technical tasks, including but not limited to correction to an application's source code needed to repair and correct logical and technical defects discovered after the original deployment).

Moreover, the additional income could also be used, through adaptive and preventive maintenance activities, to keep improving the Dashboard according to users' feedback, e.g. by leveraging all eventual new CDS products and databases, increasing climate data resolution, developing and implementing new relevant indicators, etc.

5. Conclusions

The MED-GOLD Horizon 2020 project aimed to demonstrate the added value of climate services for traditional agri-food Mediterranean systems. For the Wine sector, one of the most relevant questions raised in the project was: Where can climate services add value to the decision making process of wine companies and farmers when climate information is conveniently tailored and presented in a user-friendly manner? One of the main outcomes of the project was the MED-GOLD dashboard which provides essential climate variables, as well as bioclimatic indicators, in a simple-to-understand and easy-to-use manner.

The three bioclimatic indicators, SprR, SU35, and WSDI, analyzed in this study have been co-developed to provide actionable climate knowledge to help mitigate fungal diseases; allowing for early procurement of fungicide products and the hiring of labor for canopy management.

In this climate service oriented paper we developed an approach to determine an acceptable annual fee for a micro holding grape growers to access the seasonal forecasts of the three bioclimatic indicators on the MED-GOLD dashboard. To determine the fee, first, we calculated the seasonal forecast hit-rate, false-alarm rate, and accuracy of these three indicators over the Douro Valley wine region. Second, we performed a cost-benefit analysis identifying the potential savings and losses of a micro holding grape grower.

Table 11
Annual income generated based on 30 % and 50 % market uptake of Douro holding distributions (Fig. 2) multiplied by an annual climate service fee of €20.

	Market Uptake of Holding Distributions	
Farm Size	30 % Market Uptake	50 % Market Uptake
⩽1 ha	€71,700	€119,500
>1 to ⩽2 ha	€19,332	€32,220
>2 to ⩽5 ha	€16,104	€26,840
>5 to ⩽10 ha	€6,180	€10,300
>10 to ⩽20 ha	€2,880	€4,800
> 20 ha	€1,602	€2,670
Total Annual Income	€117,798	€196,330

Table 10
Range of potential savings of the Pro-Active Farmer, compared to the Reactive and Prepared Farmers, for a hotter- and/or wetter-than-normal year, for a 1 ha holding.

				Proposed Fee		
	Savings Range 1 to 10 Sprays	Avg. Savings 3 to 6 Sprays	10% of Avg. Savings	90% accuracy	70% accuracy	50% accuracy
Pro-Active Farmer vs. Reactive Farmer	€175–768	€406	€40	**€36**	**€28**	**€20**
Pro-Active Farmer vs. Prepared Farmer	€194–636	€275	€28	**€24**	**€19**	**€15**

The results showed SEAS5 seasonal forecasts of the three bioclimatic indicators, for hotter- and/or wetter-than-normal conditions, starting in March have an accuracy of 54–60 % compared to the ERA5 reanalysis over the Douro region. These forecast accuracies were better than assuming the upcoming season will be similar to the climatic average (a. k.a. "normal"). As such, we can see that this climate service adds value to the traditional agri-food system. Micro holding farmers over can benefit from the actionable climate knowledge as a result of the SEAS5 accuracy.

Of the three indicators, despite having a lower hit-rate, the overall seasonal forecasts of SprR performed better than SU35 and WSDI because it had lower false-alarm rates. The most accurate forecasts are those starting in June, however, correct as they may be, they bring little value to procure better pricing in products or labor.

The results of the cost-benefit analysis showed that the cost of inaction due to fungal diseases and sunburn ranges from €627–941/ha using the Market Value approach and €522–783/ha using the European Commission Standard Output approach. When the seasonal forecasts of the bioclimatic indicators are included in the decision making process, they can save a farmer more than 10 % of the annual income from a harvest for an average year. Similarly, more than 15 % of the annual income from a harvest can be saved in a hotter- and/or wetter-than-normal year. These values represent what could be saved when the seasonal forecast accuracy is 100 %, however, potential losses due to false-alarms (24 %-44 % in March) must be accounted for.

After taking into consideration the financial loss due to fungal diseases and sunburn (Section 4.2.1), the maximum potential savings of a seasonal forecast in terms of early procurement of labor and fungicide (Section 4.2.2), and the accuracy of the seasonal forecast starting in March (Section 4.1) over the Douro region, which is closer to 50 % rather than 100 %, we propose a Climate Service Fee of €20/year.

Based on this analysis, a climate service that correctly forecasts the infections risk:

- 90 % of the time should cost €24–36.
- 70 % of the time should cost €19–28.
- 50 % of the time should cost €15–20.

The approach used to determine the proposed climate service fee can be adjusted as performance of the seasonal forecast improves, in terms of hit-rate, false-alarm rates, and overall accuracy. As the seasonal forecast accuracy improves, so does its value to grape growers. The value to grape growers can increase with further developments or iterations of the MED-GOLD Dashboard. Best practices for climate service may include providing performance metrics (such as hit-rate, false-alarm rate, and accuracy) alongside their products in a transparent manner to instill a user's confidence.

The methodology presented in this paper can be extended to the valuation of other MED-GOLD Dashboard indicators (e.g. sanitary risk), regions (e.g. Italy), and time periods (e.g. climate projections). Elements of the methodology which can be generalized for the purpose of determining a user fee include: (i) evaluating the performance of a prediction; (ii) evaluating the financial impact and potential savings of a decision based on different forecast accuracies; (iii) linking the fee to the performance of the service; and (iv) transparent discussions regarding costs from the perspective of both the application user and software developer regarding maintenance. As such, a similar valuation can be performed for other MED-GOLD products created for the Olive and Durum Wheat industries. The annual income generated by the access fee for the seasonal forecast described in this paper would be only one contribution to the total income generated to maintain the MED-GOLD Dashboard.

Lastly, given the proposed fee, the distribution of holdings, and assumed Market Uptake of farmers of the Douro wine region, we showed the annual income generated can easily cover the maintenance of the MED-GOLD Dashboard. This allows surplus revenue to be used for improving the Dashboard according to users' feedback, as well as developing and implementing new relevant indicators, and leveraging new CDS products and databases.

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CRediT authorship contribution statement

Christine Nam: Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Laura Teresa Massano:** Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Antonio Graca:** Conceptualization, Writing - review & editing. **Rossana Cotroneo:** Formal analysis, Writing - original draft, Writing - review & editing. **Alessandro Dell'Aquila:** Conceptualization, Writing - original draft, Writing - review & editing, Project administration, Funding acquisition. **Federico Caboni:** Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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