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

Laura Massano<sup>a,\*</sup>, Giorgia Fossier<sup>a</sup>, Marco Gaetani<sup>a</sup>, Benjamin Bois<sup>b,c</sup>

<sup>a</sup> Scuola Universitaria Superiore IUSS, Pavia, Italy

<sup>b</sup> Centre de Recherches de Climatologie, UMR6282 Biogéosciences, CNRS / Université de Bourgogne Franche-Comté, Dijon, France

<sup>c</sup> Institut Universitaire de la Vigne et du Vin, Université de Bourgogne, Dijon, France

## 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

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

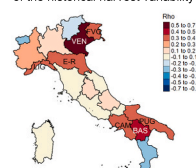
Different factors influences grape productivity



Bioclimatic indices can partially explain the total variability of grape productivity

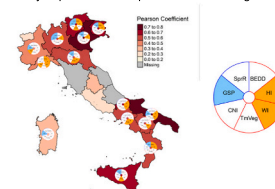
The Investigation is performed at with raw and detrended data using single and multi-regressive approach

Bioclimatic indices explained up to 45 % of the historical harvest variability



HI - raw data

Multi-regressive approach increases the portion of variability explained in comparison with the single index



Pearson correlation of productivity observed and modelled by multi-regressive best model

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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 significant results in region where the single regression is not statically significant.

\* Corresponding author.

E-mail address: [laura.massano@iusspavia.it](mailto:laura.massano@iusspavia.it) (L. Massano).

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 (Köppen-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 Acquotta, 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 estimate 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)	$HI = K \sum_{01\ Apr}^{30\ Sep} \max \left[ \left( \frac{T_{mean} - 10}{2} + (T_{max} - 10) \right); 0 \right]$ 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)	$SprR = \sum_{21\ Apr}^{21\ Jun} Prec_{min}$	–

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; Raúl 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 ( $y = a \cdot \text{Index1} + b \cdot \text{index2} + c \cdot \text{index3}$  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 ( $\text{AdjR}^2$ ), 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

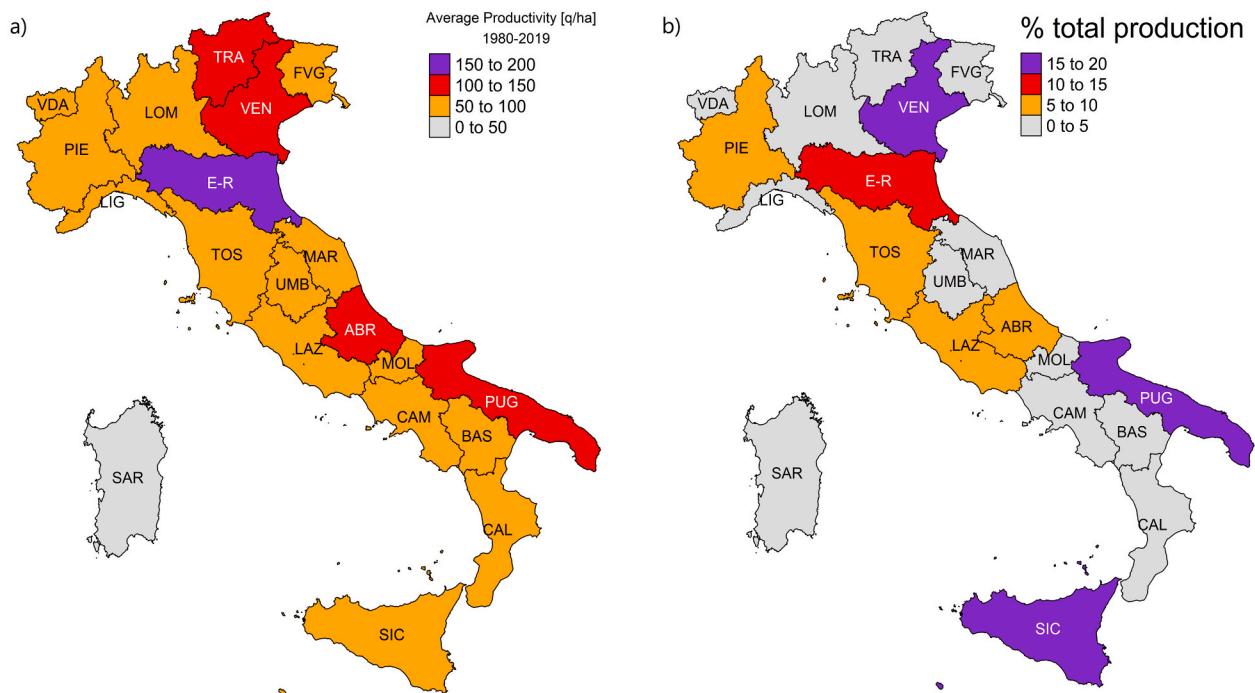
### 2.1. Grape productivity in Italy

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 (Samari, 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 homogeneous 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 ( $\rho$  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 Kendall 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 significant trend ( $p \leq 0.05$ ).

Region	Cod. Reg.	Productivity		BEDD		HI		WI		Tm Veg		CNI		GSP		SprR	
		Z	Sen's Slope [(g/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	6.33*	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  $\text{adj}R^2$ ) 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 multi-regressive 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 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).

#### 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

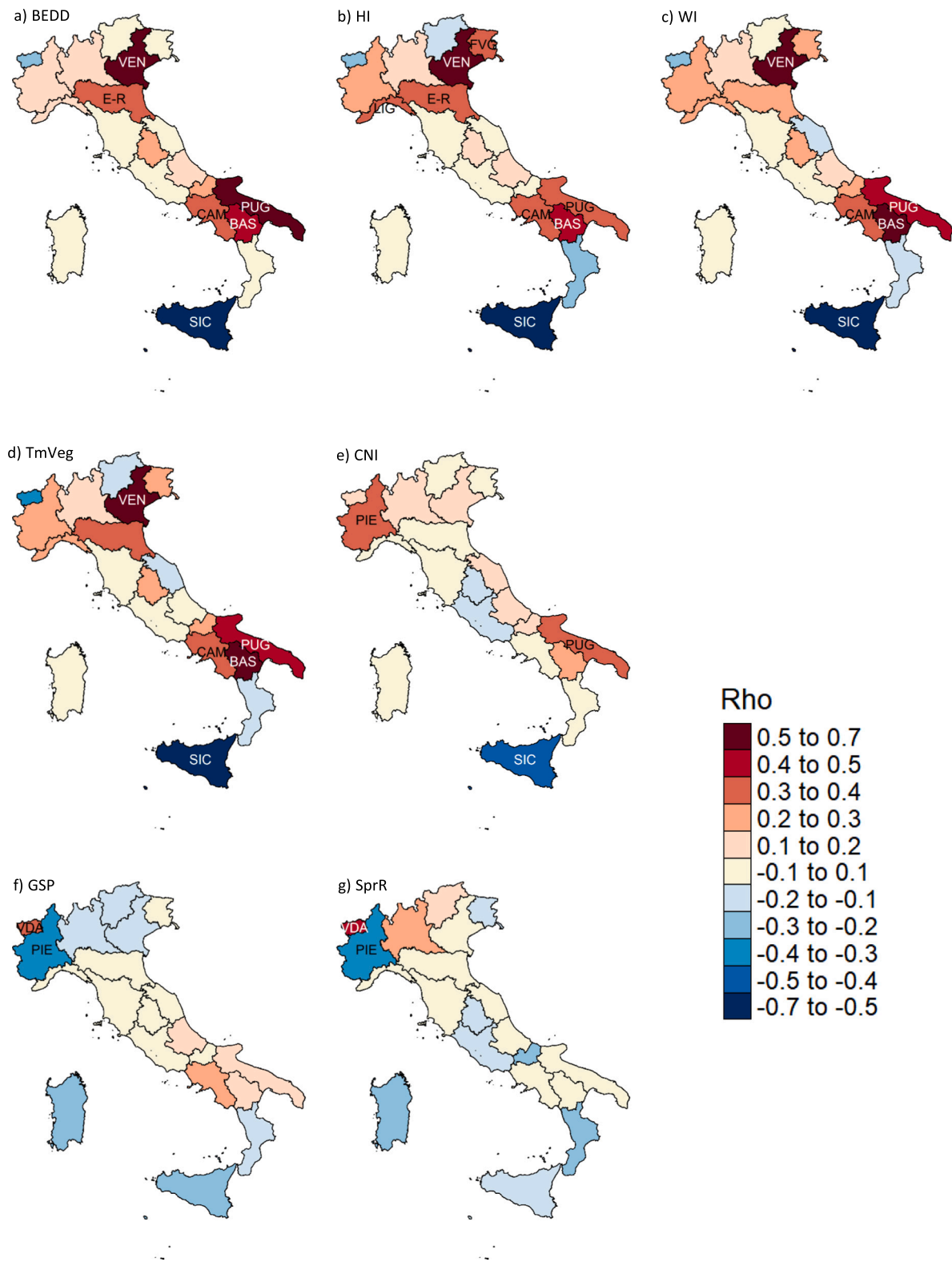


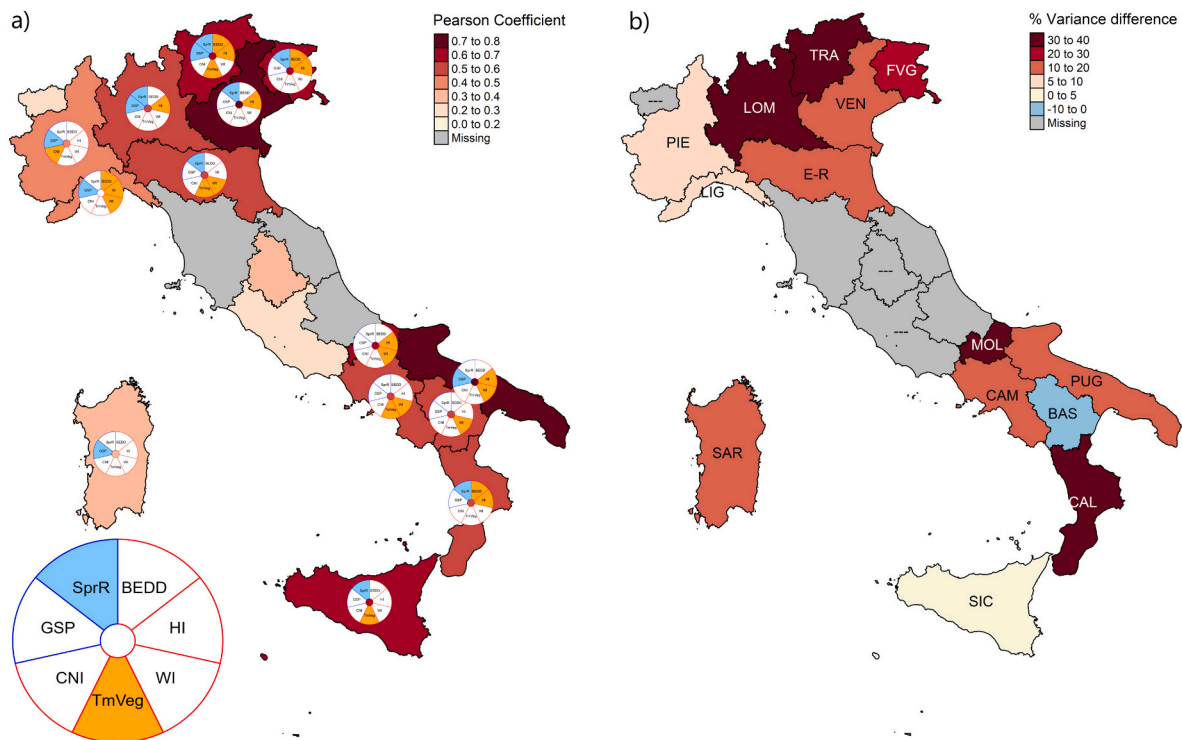
Fig. 2. Maps of Italy showing the Spearman correlation coefficient between the observed productivity and the bioclimatic indices (raw data). The regions where correlations are significant are labelled.

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 where the multi-regressive model has no skill, i.e. low AdjR<sup>2</sup>. 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 “—”).

### 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.

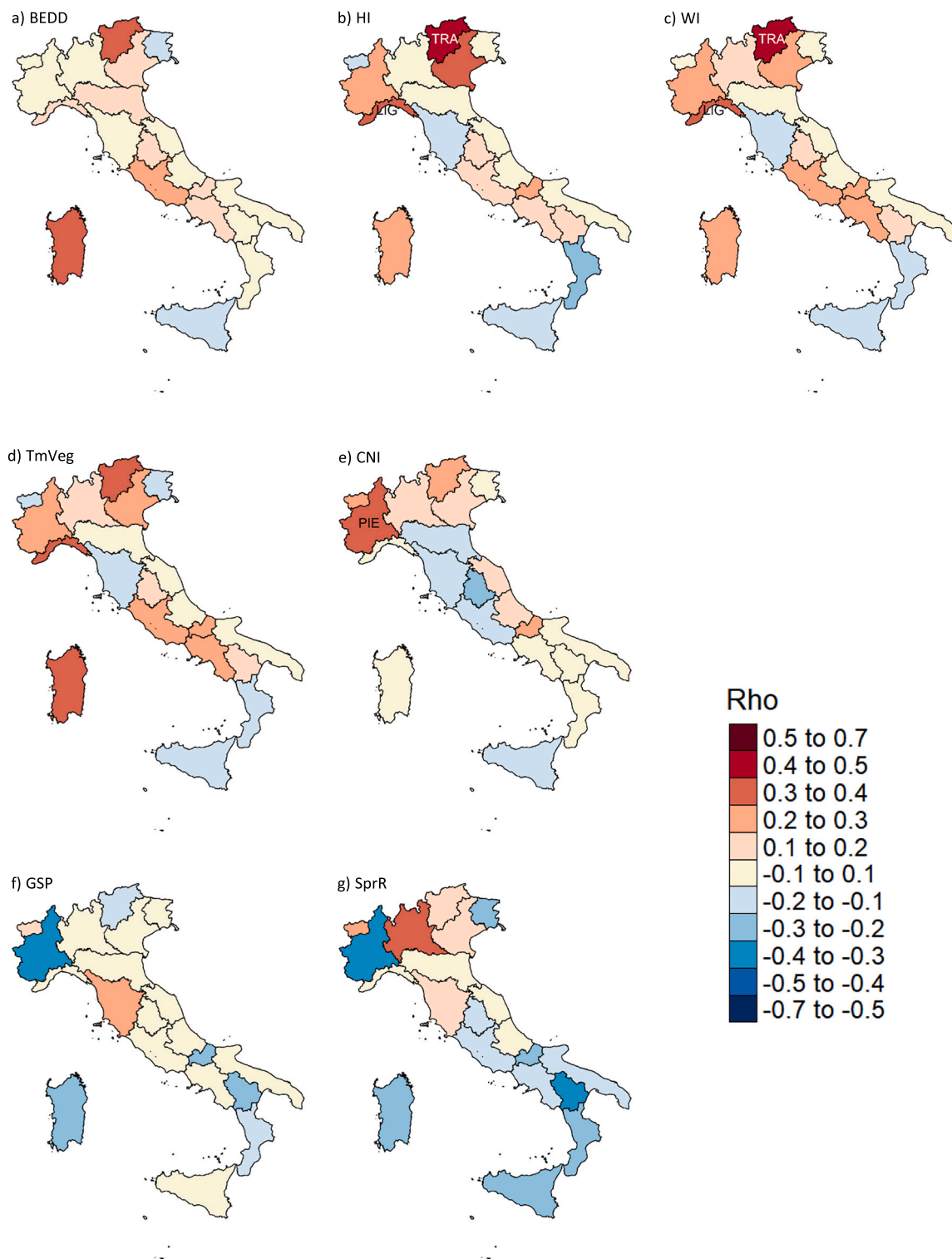
Overall, the interannual climate variability impacts less on

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

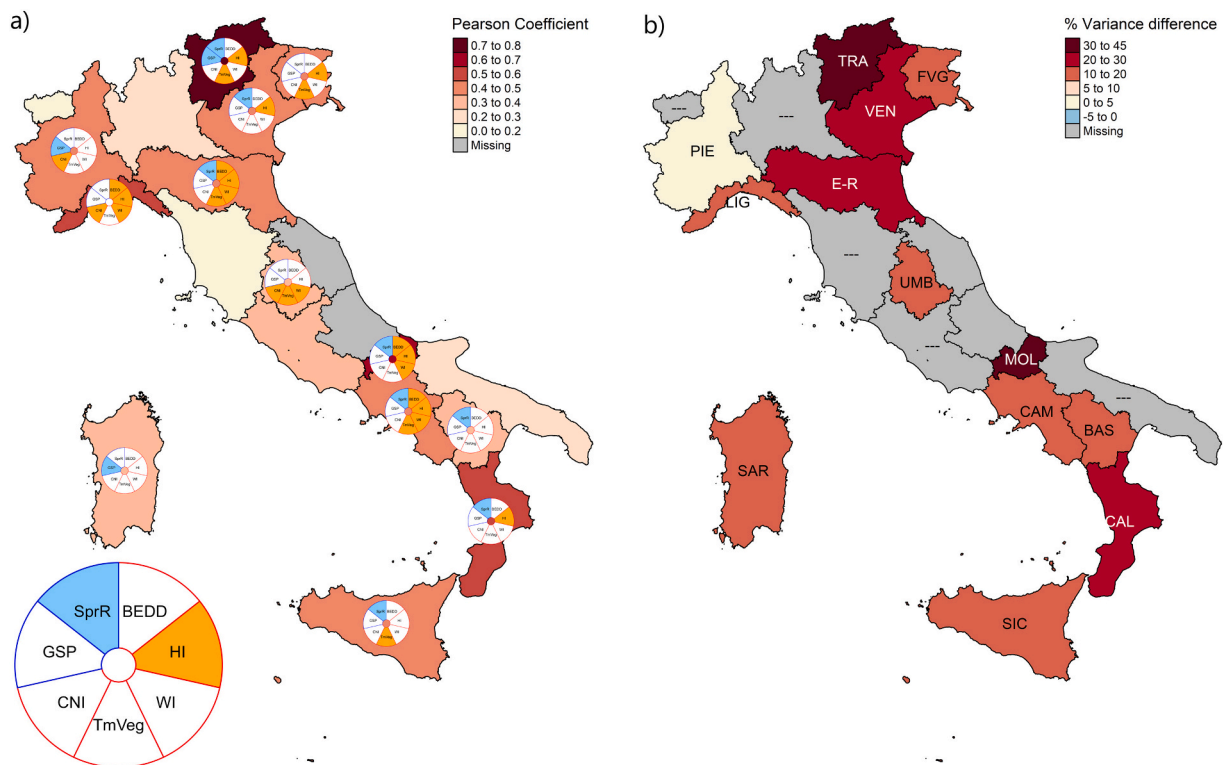


**Fig. 4.** As Fig. 2, but at interannual time scale. Maps of Italy showing the Spearman correlation coefficient between the observed productivity and the bioclimatic indices (raw data). The regions where correlations are significant are labelled.

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>.



**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<sup>2</sup>. 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 Fossier:** 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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