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Grapevine productivity and weather fluctuation: evidence for Italian regions (2006–2024)

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Abstract

The wine sector holds substantial economic importance in the Italian agri-food production system, that is nonetheless exposed to the effects of climate change displaying heterogeneous effects between cultivated varieties and geographical regions. Using daily weather variables (maximum/minimum temperatures and precipitation) aggregated over the annual grapevine growth cycle, this paper investigates the impact of interannual growing-season weather variability on grapevine productivity in Italy at a regional level from 2006 to 2024. Moreover, an innovative reconstruction of two agro-meteorological indicators is developed, namely (a) standardized weather indexes and (b) degree days as growing degree days (GDD), killing degree days (KDD) and frost degree days (FDD), specifically designed to capture both seasonal and nonlinear responses to temperature and precipitation. Fixed-effects panel models are used to link productivity to weather variability, controlling for unobservable variables and potential nonlinearities. Results confirm nonlinear temperature effects; in particular, productivity increases with temperatures up to roughly 31–33°C, but going over this threshold is very harmful. Moreover, the results indicate that very low minimum temperatures, captured by the FDD indicator, have a negative effect on productivity (frost damages). Precipitation has different impacts depending on the growing season. Higher precipitation in April–June tends to reduce productivity, whereas in the generally drier July–September period additional precipitation supports productivity up to a point, beyond which it becomes detrimental.

Keywords: Climate change, Agricultural wine sector, Grapevine productivity, Nonlinear temperature effect, Weather fluctuation

Introduction

Agriculture is one of the sectors most exposed to the physical risk generated by climate change since temperature and rainfall are both determining factors for crop production (Deschênes and Greenstone 2007). Agricultural systems in several countries, are highly susceptible to the consequences of climate change with the Mediterranean region, including Italy, being particularly vulnerable (Wiebe et al. 2015). Climatic conditions play a crucial role in wine production, a sector where Italy plays a role of leader on a worldwide scale. For this reason, it is important to realize the consequences it can have on the wine industry, as climatic variability can alter both the ripening times of grapes and the growing capacity in certain regions (Grazia et al. 2023). The International Organisation of Vine and Wine (henceforth OIV) estimated world wine production, in 2025, to be between 228 and 235 million hectoliters. This represents a 3% increase compared with the low volume recorded in 2024, yet it remains around 7% below the five-year average (International Organisation of Vine and Wine 2025). In fact, grapevine yield is largely dependent on climatic conditions, particularly during the growing season (Urhausen et al. 2011; Van Leeuwen et al. 2004). Furthermore, climate change affects regional growing conditions, such as: (i) the timing of the main phenological phases; (ii) the duration of the growing season; (iii) daily temperatures and the number of growing degree days. Vine phenology and harvest dates are significantly associated with climate, and the impacts of climate change are evident in many wine-growing regions (Briche et al. 2014).

Moreover, climate change predictions also indicate considerable changes in both temperatures and precipitation in the growing season in the coming decades (Fraga et al. 2012). As numerous studies have proven, weather variables are key drivers in determining agriculture production yields (Chevet et al. 2011). Gladstones (1992) estimates that, once technological factors are controlled, climate is the major determinant of grape yield.

Several contributions describe the connection between climate change and the wine sector in Italy, focusing on temperature and rainfall impacts. Moriondo et al. (2011), which examined the impact of climate change on viticulture in Tuscany, show that the gradual increase in temperature and the reduction in rainfall determine a gradual decline in the final yield and a reshape of production areas towards higher altitudes locations. Teslić et al. (2019) evaluated the impact of climate change on viticulture in Emilia-Romagna (Northern Italy) and Sacchelli et al. (2017) reported a reduction in revenues and financial damage due to weather-related decreased yields in the Tuscany region. Massano et al. (2023) investigate how both long-term change and natural variability of the bioclimatic indices impacted grape productivity in Italy. They conclude that bioclimatic indicators can be used as a proxy for grape productivity providing a simple tool that grape growers, wine consortia and policy makers can use to adapt to future climate. Evidence from these articles leads to foresight on future negative impacts of climate change on the viticulture sector in Italy and the need for adaptation measures to protect the yields and the quality of grapes.

From a meteorological standpoint, it is well understood that weather refers to day-to-day atmospheric conditions, whereas climate describes the statistical characteristics of an area over longer periods. In line with the climate–economics literature, however, this paper follows the standard distinction between weather and climate adopted in empirical studies such as Schlenker and Roberts (2009); D'Agostino and Schlenker (2016); Accetturo and Alpino (2023). Climate refers to the long–run distribution of atmospheric conditions in a given location (long-term and greater moments of temperature and precipitation), while weather denotes the short-run realization drawn from this distribution in a specific period, such as the conditions observed in a specific growing season.

This article provides an empirical assessment of the impact of climate change on the wine sector in Italy, identifying how weather fluctuations may affect production and contributing to the growing empirical literature in wine economics on climate-related effects on wine production. The empirical analysis focuses precisely on interannual growing-season weather fluctuations around each region's underlying climate, by using panel data methods.

Recent years have seen an increase in the number of assessments of climate change impacts on agriculture that increasingly refer to panel models to examine the relationship between agricultural yields and weather fluctuations (Larsen et al. 2015). Panel data models have proven (Schlenker and Roberts 2009; Haqiqi et al. 2021; D'Agostino and Schlenker 2016) to be suitable to investigate nonlinearities in the connection between weather and agricultural yield (corn, wheat, rice and soybeans). It has been shown by Accetturo and Alpino (2023) that statistical agricultural model based on panel studies can be applied to grapevine, linking weather fluctuations to this crop yield. They consider weather data according to the growing period from April to September, showing that high temperatures can become harmful when they exceed around 30° and total water requirements vary between 500 and 1200 mm, depending mainly on climate and length of the growing period. Also, Lamonaca et al. (2021) examined the linkage between climate change and productivity levels in the global wine sector, finding that grapevine yield is affected by higher temperatures during the summer, while rainfall has a variable impact depending on the vine growth cycle. Recent work has also examined the economic consequences of climate stress in Italian viticulture. Moreover, Grazia et al. (2025) document a nonlinear relationship between temperature, precipitation and farm-level revenues using a Ricardian framework, highlighting increasing profitability losses beyond thermal thresholds, especially in Southern Italy.

To the best of our knowledge, there are no studies that have applied panel data methods to grapevine yields in Italy, leaving a gap in the literature. In addition, this is one of the first studies that employs regional panel data combining daily JRC MARS weather observations with ISTAT grapevine yields for all 20 Italian regions over 2006–2024, in order to investigate the relationship between interannual growing-season weather variability and grapevine productivity in Italy. Weather variability is measured by constructing weather indicators explicitly aligned with the phenological phase of the annual vine cycle, including standardized weather indexes and degree days for heat and frost, namely growing, killing and frost degree days (henceforth GDD, KDD and FDD). Few authors have applied this methodology to grapevines, especially in the Italian wine industry. The analysis is focused on the Italian wine agricultural sector because the distinguished role of the country in the global wine production features it as a case study for analyzing the impacts of climate variability (Bozzola et al. 2018). Research in this area is of great interest and includes a very active research community, particularly because Italy's vulnerability may be mainly due to its geographical position and heterogeneous climatic conditions, with a predominance of heat waves and a high variability and uneven rainfalls (Olper et al. 2021).

The remainder of this work is structured as follows. Section 2 describes the data; Sect. 3 provides information on the study area and climate background; Sect. 4 illustrates the methodology; Sect. 5 presents the results; Sect. 6 presents the discussion and Sect. 7 concludes.

Table 1 Sources of data. Source: JRC Agri4cast MARS Meteorological Database; Italian National Statistics Institute (ISTAT)

Source of data	Data acquired	Frequency	Time period	Spatial coverage
JRC Agri4cast MARS Meteorological database	Precipitation (mm) Maximum temperature (°C) Minimum temperature (°C)	Daily	1979–2024	25×25 km grid aggregated to Italian regions
ISTAT	Vineyard area (ha) Harvested production for grapevine (q)	Annual	2006–2024	Italian regions

Data

The impact of growing-season weather variables on grapevine productivity was estimated using information about precipitation and temperature for each Italian region. Agricultural data on the vineyard area and harvested production for grapevines were collected from the Italian National Statistics Institute (ISTAT) from 2006 to 2024. Vineyard area measures the total hectares (ha) of an area under vine cultivation, while grape production represents the total quantity of grapes harvested, expressed in quintals (q). Thus, the grapevine productivity was calculated as the ratio between the production (q) over the total hectares (ha). Data on daily precipitation (in millimeters, mm) and on maximum and minimum temperatures (in °C) for the period 1979–2024 were extracted from the JRC Agri4cast MARS Meteorological Database, a gridded database with 25× 25 km cells which covers the European Union and neighboring countries. Grid-cell values were first mapped to Italian provinces by matching each cell to the province in which its centroid lies. For each province and day, weather variables were computed as the mean of all grid cells assigned to that province. Daily provincial series were then aggregated to the regional level by taking the average across provinces within each region. These regional daily series formed the basis for the construction of the growing-season indicators described in Sect. Data processing and vine growth cycle. Table 1 provides a summary of the datasets used in the analysis.

Data processing and vine growth cycle

Several authors have described crop conditions using weather variables defined over the growing season of a specific crop (Porter and Semenov 2005). For grapevine, the annual vine growth cycle is divided into two seasons, from April to June and from July to September, according to shoot length and cluster formation, each with their respective phases depicted in Table 2 (Hellman 2003; Giese et al. 2020). The budbreak phase begins in April, as the vine begins to vegetate again, the shoots begin to grow rapidly. Flowering occurs in May, and the flowers open, marking the beginning of the reproductive phase. This is a critical stage, as fertilization of the flowers will determine the formation of the clusters. Finally, shoot growth occurs in June. The shoots grow vigorously, and the first leaves expand. During this period, the plant accumulates energy through photosynthesis, which is essential for sustaining the next stages. In July, the fruit set phase occurs, in which the flowers transform into small fruits, called berries. This stage indicates the beginning of cluster development. The veraison occurs in August, when the berries begin to change color and ripen. This process is visible through the changing

Table 2 Annual vine growth cycle and weather requirements. Source: Authors' elaborations from Hellman, 2003; Giese et al., 2020; and Accetturo et al., 2023

Annual vine growth cycle											
Resting	Resting	Resting	Budbreak	Flowering	Shoot growth	Fruit set	Veraison	Ripening	Harvest	Resting	Resting
Weather requirements											
			Fresh spring, Frost sensitivity, Moderate rainfall			*Hot summer sensitivity, Low rainfall*					
JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC

colors of the berries, which change from green to yellow, red or purple, depending on the variety. Finally, the ripening stage occurs in September, when the berries reach full maturity, accumulating sugars and developing their characteristic flavor. This stage is crucial in determining the quality of the wine that will be produced. Ripening is followed by the harvest, which usually takes place in late September or early October. Grapevine can grow where conditions are very heterogeneous but typically require cool springs and summers without excessive heat. Water requirements can also differ greatly depending on the type. Consequently, grapevine can be cultivated almost anywhere in Italy (Accetturo and Alpino 2023). Negative temperatures during spring may damage developing buds and leaves/shoots (Branas 1974; Hidalgo 2002). Moreover, a base temperature of 10°C is the minimum threshold required for the grapevine to start its growth cycle (Amerine and Winkler 1944; Winkler 1974). On the other hand, very high temperatures (above 40–45°C) can affect certain physiological processes irreversibly (Berry and Bjorkman 1980), leading to poor grape yield (Kliewer 1977; Mullins et al. 1992).

Furthermore, annual precipitation and its seasonal distribution are also critical factors influencing viticulture in the various stages of development (Austin and Bondari 1988). Additionally, high humidity in the soil is required during budbreak and shoot development, followed by dry and stable weather conditions from fruit flowering to berry ripening (Jones and Davis 2000; Ramos et al. 2008).

Considering these phenological stages and weather requirements, daily meteorological observations were aggregated into growing season measures that explicitly reflect the vine growth cycle. Specifically, daily data from the JRC Agri4cast MARS database were clustered into the April–September growing season and split into two three-month sub-periods: season 1 (s_1), April–June (budbreak, flowering, shoot growth) and season 2 (s_2), July–September (fruit set, veraison, ripening). As to the precipitations, the growing season weather variable was constructed as the sum of daily precipitation (mm) over the semester April-September and, separately, for each of the two three-month sub-periods, capturing the total water supply during the corresponding phenological stage. As to maximum and minimum temperatures, daily regional observations were aggregated by computing the average value over the period April to September, then, for each of the two subperiods (s_1: April–June, s_2: July–September), the maximum value was defined as the highest of the three monthly mean maximum temperatures and the minimum temperature was the lowest of the three monthly mean minimum temperatures. Table 3 presents the data aggregation method. In addition, based on these two seasonal measures

Table 3 Data aggregation method. Source: Authors' estimation from Climate Change Knowledge Portal and Italian National Statistics Institute (ISTAT) data

Weather variables	Season	Season 1	Season 2	Method of aggregation
Precipitation (mm)	April September	April June	July September	Sum of the daily precipitation for each season
Maximum Temperature (°C)	April September	April June	July September	Highest of the three monthly mean maximum temperatures
Minimum Temperature (°C)	April September	April June	July September	Lowest of the three monthly mean minimum temperatures

for each region and year, two agro-meteorological indicators widely used in the agricultural literature were computed (Tigkas et al. 2019):

(i) Standardized weather indexes (for precipitation and temperatures)
(ii) Degree days measures, (GDD, KDD and FDD).

Through the use of these indicators it was possible to quantify both deviations from long-term climate averages and the cumulative exposure to beneficial or harmful temperatures over the vine's growing season.

Standardized weather indexes

In this section the procedure used to construct the standardized weather index for each region/year of the sample is illustrated. The index is a measure of how far a given weather observation deviated from its long-term seasonal average, measured over the period 1979–2024. These deviations from the historical mean were standardized by the corresponding historical standard deviation, providing a dimensionless measure of how anomalous each seasonal value is relative to the region-specific climatic baseline. Following Makate et al. (2024), the standardized precipitation index is defined as the normalized deviation of cumulative precipitation in each season from its expected seasonal level, as given by the long-term historical average. Consequently, the precipitation index is defined as follows:

$$\widehat{\text{Precip}}_{it,s} = \frac{\text{Precip}_{it,s} - \overline{\text{Precip}}_{i,s}}{\sigma_{i,s}^{\text{Precip}}} \tag{1}$$

where $\widehat{\text{Precip}}_{it,s}$ denotes the standardized precipitation index for region i in year t and season s, and $\text{Precip}_{it,s}$ is the observed amount of precipitation in season s (with $s = 1, 2$). $\overline{\text{Precip}}_{i,s}$ represents the historical average seasonal precipitation for region i over the period 1979–2024, while $\sigma_{i,s}^{\text{precip}}$ is the standard deviation of precipitation for the same region and season over the same period. Likewise, the standardized temperature indices were computed as Z-scores, with negative (positive) values indicating seasons that were drier/cooler (wetter/warmer) than the long-term regional average.[1]

$$\widehat{T\,\max}_{it,s} = \frac{T\,\max_{it,s} - \overline{T\,\max}_{i,s}}{\sigma_{i,s}^{T\,\max}} \tag{2}$$

$$\widehat{T\,\min}_{it,s} = \frac{T\,\min_{it,s} - \overline{T\,\min}_{i,s}}{\sigma_{i,s}^{T\,\min}} \tag{3}$$

Therefore, the indexes in eqs. (2) and (3) measure interannual anomalies around this climatic baseline for each region/year.

[1] Standardized weather variables plots are depicted in Appendix A.

Growing and killing degree days

The nonlinear relationship between temperature and crop yields has been widely documented in the literature (Schlenker and Roberts 2009) using the concepts of Growing Degree Days (GDD) and Killing Degree Days (KDD).[2] Degree days (GDD and KDD) measure the cumulative time during which a crop is exposed to temperatures within (outside) specific lower and upper limit, then summing these daily temperature exposures over a fixed growing season (from April 1 to September 30), to obtain a measure of annual growing (killing) days (Schlenker and Roberts 2009; Burke and Emerick 2016; Blanc and Schlenker 2017). In this paper, the non-linear relationship was captured through three degree days indicators constructed from daily JRC Agri4cast MARS data: Growing Degree Days (GDD), Killing Degree Days (KDD) and Frost Degree Days (FDD). Let $T\max_{\mathrm{itd}}$ and $T\min_{\mathrm{itd}}$ denote the daily maximum and minimum air temperatures (in °C) for region i in year t on day d. Let T_{L} be the lower base temperature at which grapevine growth starts, T_{U} the upper critical threshold above which additional heat becomes harmful, and T_{F} a frost-damage threshold. Daily GDD, KDD and FDD are defined as:

$$\mathrm{GDD}_{itd} = \begin{cases} 0, & \text{if } \frac{T\max_{itd} + T\min_{itd}}{2} \leq T_{\mathrm{L}} \\ \frac{T\max_{itd} + T\min_{itd}}{2} - T_{\mathrm{L}}, & \text{if } T_L < \frac{T\max_{itd} + T\min_{itd}}{2} < T_{\mathrm{U}} \\ 0, & \text{if } \frac{T\max_{itd} + T\min_{itd}}{2} \geq T_{\mathrm{U}} \end{cases} \tag{4}$$

$$\mathrm{KDD}_{itd} = \begin{cases} 0, & \text{if } T\max_{itd} \leq T_{\mathrm{U}} \\ T\max_{itd} - T_{\mathrm{U}}, & \text{if } T\max_{itd} > T_{\mathrm{U}} \end{cases} \tag{5}$$

$$\mathrm{FDD}_{itd} = \begin{cases} 0, & \text{if } T\min_{itd} \geq T_{\mathrm{F}} \\ T_{\mathrm{F}} - T\min_{itd}, & \text{if } T\min_{itd} < T_{\mathrm{F}} \end{cases} \tag{6}$$

Seasonal indicators GDD_{it}, KDD_{it} and FDD_{it} were obtained by summing the daily contributions over the April-September growing season. Most studies in the literature assume that high temperatures are damaging, although the severity of the damage remains uncertain (Schlenker and Roberts 2008).

It is obvious that the specific measure of the GDD/KDD/FDD is largely dependent upon the set critical threshold. According to agronomists, rapid shoot development begins when average daily temperatures are around 10°C. High temperatures can become harmful when they exceed around 32°C. In the empirical application, the baseline specification sets $T_{\mathrm{L}} = 10^{\circ}\mathrm{C}$ and $T_{\mathrm{U}} = 33^{\circ}\mathrm{C}$, in line with agronomic evidence that rapid shoot development in grapevine begins around 10°C and that heat stress becomes severe above about 32°C (Amerine and Winkler 1944; Mullins et al. 1992; Schlenker and Roberts 2009).

The frost threshold is set at $T_{\mathrm{F}} = -3^{\circ}\mathrm{C}$, consistent with studies documenting substantial frost damage around the level of −2°C for perennial crops (Vitasse and Rebetez 2018; Santeramo and Russo 2021). As a robustness check, alternative upper bounds between

[2] In the literature three different methods are used to calculate degree days, i.e., 1) Averaging Method; 2) Baskerville-Emin (BE) Method; and 3) Electronic Real-time Data Collection. In this study, degree days are computed using the Averaging Method.

27°C and 33°C and frost thresholds between 3°C and −3°C were considered. The intuition is that temperatures between T_L and T_U are generally considered to increase yield, while temperatures above T_U and below T_F decrease yield.

Study area and climate background

The wine sector holds substantial economic importance in the Italian agri-food production system. When considering the value of agricultural production alone, which exceeded 77 billion euros in 2023, wine products (excluding wineries) accounted for 8% (CREA 2024). Italy registered a significant reduction in the volume of its wine production in 2023, estimated at 43.9 million hectoliters (−12% compared to 2022); this was the lowest production since the historically small yield of 2017 (International Organisation of Vine and Wine 2023). Moreover, the International Organisation of Vine and Wine (2025) estimate Italian wine production in 2025 at 47.4 million hectoliters, an increase of about 3.3 mhl (+8%) compared with 2024 and roughly 2% above the recent five-year average. This partial rebound, supported by a mild spring, balanced rainfall and a summer that was not excessively hot, nevertheless followed two unusually low harvests and highlights the growing interannual volatility of Italian wine output. Many factors could have influenced this low production; specifically, several Italian wine-growing areas were affected by heavy rains, floods, hailstorms and drought.

Situated in the Mediterranean Sea with a morphological formation that is typically mountainous and hilly, with numerous short rivers, Italy has a climate characterized by seasonal droughts and highly concentrated rainfall in specific periods. These aspects, in the context of significant climatic anomalies, can create serious damage to the economic viability of agricultural activities since economic decisions are also influenced by the increased variability of atmospheric phenomena. Wine production is common in all regions with diverse local viticultural systems, influenced by the nexus between soil, microclimate and variety. These interactions are very susceptible to climate change risks; in particular, year-to-year fluctuations in growing-season weather conditions pose a significant yield risk, generating variability in grape and wine output and affecting production costs (Seccia and Santeramo 2018).

Figure 1 summarizes the spatial patterns of grapevine productivity and growing-season climate over the period 2006–2024. The upper-left panel reports the average regional grapevine productivity, measured as annual grape production per hectare of vineyard area under vine cultivation (q/ha), constructed from ISTAT data. The remaining panels display, for each region, the average cumulative precipitation over April–September (upper-right panel) and the average April–September minimum and maximum temperatures (lower-left and lower-right panels, respectively), based on daily observations from the JRC MARS Agro-Meteorological Database aggregated at the regional scale. Precipitation is expressed as total rainfall (mm) accumulated over the growing season, while temperatures represent the seasonal averages of daily minimum and maximum air temperatures (°C). The productivity map highlights substantial spatial heterogeneity. Regions such as Puglia, Veneto and Emilia-Romagna display the highest average grapevine productivity, with values well above 120 q/ha, whereas several southern, island and mountainous regions (e.g. Sardegna, Sicilia, Calabria, Basilicata, Valle d'Aosta) exhibit markedly lower yields. These differences likely reflect the combined influence of

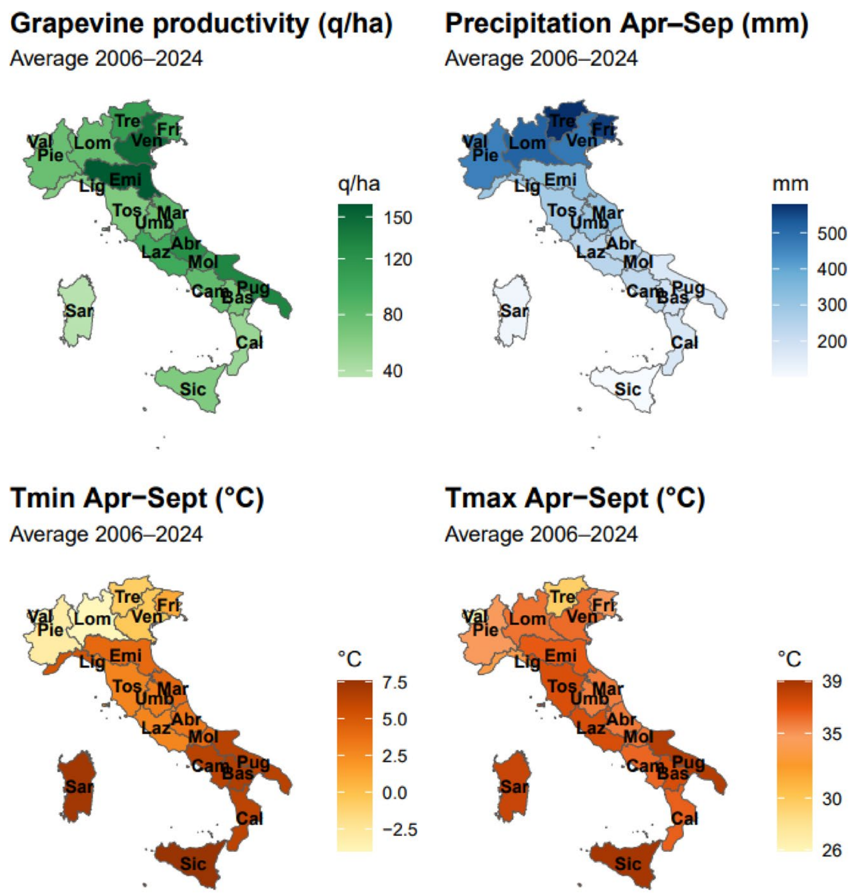

Fig. 1 Average grapevine productivity and growing-season climate in Italian regions (2006–2024)

agro-climatic conditions, soil characteristics, varietal composition and production systems. Growing-season precipitation shows a clear north–south gradient. Alpine and northern regions (e.g. Valle d'Aosta, Piemonte, Lombardia, Trentino-Alto Adige, Friuli-Venezia Giulia, Veneto) receive the highest cumulative rainfall over April–September, while southern and insular regions (such as Puglia, Calabria, Sicilia and Sardegna) are considerably drier. Minimum and maximum temperatures display the opposite pattern: April–September averages are lower in northern and alpine regions and increase moving southwards, with the warmest conditions observed in the southern mainland and on the islands. This configuration implies that Italian viticulture operates under a wide range of climatic settings, from relatively cool and wet environments in the north to hot and dry conditions in the south, making the assessment of growing-season weather impacts on grapevine productivity particularly relevant.

For completeness, Appendix B reports the full regional time series of grapevine productivity and growing-season weather variables over 2006–2024, providing a graphical view of their interannual evolution.

Methodology

Fixed-effects panel estimation is implemented to investigate the effects of interannual growing-season weather variability on grapevine productivity from 2006 to 2024 across Italian regions. Fixed-effects panel analysis is appropriate for understanding whether and how growing-season weather variables affect grapevine productivity in different regions. Indeed, each region has unique characteristics that could influence productivity (e.g., soil type, farming practices), therefore fixed effects allow these unobservable but consistent differences to be controlled over time. Weather conditions, such as minimum temperature, maximum temperature and precipitation, could have different impacts in different regions. For example, an increase in temperature could be beneficial in one region but detrimental in another. The time patterns observed in Appendix B indicate that some factors, potentially related to climate change or other dynamics, are affecting productivity (Blanc and Schlenker 2017).

As to the output of the production function, panel models typically use crop yields to estimate the economic impact of climate change. In contrast, the Ricardian (cross-sectional) approach uses a proxy for land productivity, such as income or profit. The vector of independent variables of a production function generally contains inputs like land, labor and capital (Oury 1965), whereas weather conditions are commonly expressed by the effect of precipitation and temperature (Barrios et al. 2008; Schlenker and Lobell 2010). Regions may differ not only in climate but also in other characteristics, such as soil quality, which may be related to climate. The use of panel models considers these aspects and, through fixed effects can absorb all influences caused by unobserved factors that do not vary over time within each group. The resulting deviations in growing-season weather conditions from their regional mean are random and exogenous (Dell et al. 2014) and are not correlated with other productivity inputs, so the absence of these inputs does not affect the coefficients of the weather variables. In practice, the model is estimated using the within transformation, i.e. by subtracting from each yearly observation the region-specific mean over the sample period, so that only within-region deviations over time identify the weather effects. This approach allows us to estimate a common marginal effect of weather on productivity across Italian regions, conditional on their different baseline levels. The model assumes that grapevine productivity is a function of weather; namely, a log–linear specification is estimated in which the dependent variable is the natural logarithm of regional grapevine productivity, defined as annual grape production per hectare of vineyard area (q/ha). The dependent variable is constructed as follows:

$$y_{it} = \ln\left(\frac{\text{Harvested}_{it}}{\text{Area}_{it}}\right) \tag{7}$$

where i is the region, t is the time, in logarithmic specification. These regional-level productivities were combined with different specifications of weather for 2006–2024. Our regression equation links log productivity $y_{i,t}$ to various weather measurements $f(w_{it,s})$. A semilog model assumes that the effect of temperature on productivity is in relative terms, i.e., a given temperature decreases/increases productivity by a given percentage independent of the baseline. This choice, in line with Schlenker and Roberts (2006, 2009), helps stabilize the variance of yields and allows for an elasticity interpretation of the estimated coefficients. The following equation is estimated:

$$y_{it} = f(w_{it,s}) + \mu_i + \gamma_1 t + \gamma_2 t^2 + \varepsilon_{it} \tag{8}$$

where $w_{it,s}$ is a vector of growing-season weather variables for region i, year t and season s (with $s \in \{s_1 : \text{April–June}, s_2 : \text{July–September}\}$), μ_i denotes regional fixed effects, t is a linear trend and t^2 is a quadratic time trend capturing overall technological progress[3]; finally, $\varepsilon_{i,t}$ captures all other unobserved variables (Schlenker and Lobell, 2010). Four specifications are used to model the impact of weather $f(w_{it,s})$:

(i) Linear specification controlling for the maximum and minimum temperature as well as for total precipitation during the two growing seasons (s_1, s_2).

(ii) Quadratic specification, where weather variables (maximum and minimum temperature and precipitation during the two growing seasons) are in quadratic form (s_1, s_2).

(iii) Standardized index specifications for all the weather variables during the two growing seasons (s_1, s_2).

(iv) Nonlinear effects of temperature, accounted for by the GDD, KDD and FDD measures, controlling as well as for precipitation during the growing season (April–September).

Results

Tables 4, 5 and 6 present the regression results of the weather coefficients in various model specifications outlined in the previous section. All regressions were estimated with robust standard errors. In linear (i), quadratic (ii) and standardized (iii) specifications of the weather, maximum and minimum temperatures were included separately to avoid multicollinearity. In all the specifications the Hausman test (Hausman 1978) was used to confirm the modelling strategy, i.e. fixed effects over the random effects.

The linear specification of the model (i), reported in Appendix C, was tested for functional form misspecification using the Ramsey RESET test (Ramsey 1969). The test rejected the null hypothesis of correct specification at conventional significance levels, indicating that the linear form may omit relevant nonlinearities. Consequently, the analysis and discussion are for model (ii) focused on the quadratic specification of the weather. The estimates include a deterministic quadratic trend (Trend and Trend^2), which captures technological growth, improvements in agricultural practices, and other factors of progress over time, allowing for a nonlinear trajectory of productivity in the long run. This trend represents an approximate average of the deterministic dynamics of production in the Italian regions. In other words, the deterministic trend represents the expected path of productivity in the absence of weather shocks, while the estimated semi-elasticities for temperature and precipitation measure the impact of short-run weather fluctuations. Regional fixed effects control for time-invariant characteristics

[3] A quadratic time trend is included, instead of year fixed effects, to model long-term technological progress in viticulture. This approach allows us to filter out yield improvements not driven by climate while preserving the identification of inter annual weather fluctuations.

specific to each region (e.g., soil type, winemaking tradition). Once controlled for the exogenous time trend and regional fixed effect, weather conditions explain deviations from expected productivity.

Results from quadratic specification of the weather

Quadratic specification (ii) is represented in Table 4, which indicates the evidence of significant non-linear effects in the linkage between growing-season weather conditions and grapevine productivity, highlighting differential effects by phenological phase. The quadratic model in Table 4 points out that maximum temperatures from April to June are not statistically significant. Conversely, during the season July-September, maximum

Table 4 Regression results: log grapevine productivity estimation in a weather quadratic specification. Source: Author's elaborations on ISTAT and JRC Agri4cast MARS Meteorological Database

Dependent variable:	**Log grapevine productivity**	
	(2a)	**(2b)**
Maximum temperature (April–June)	−0.05276	
	(0.05055)	
Maximum temperature (July–September)	0.11669**	
	(0.05395)	
Minimum temperature (April–June)		0.0052187
		(0.00455)
Minimum temperature (July–September)		0.0058024
		(0.005681)
Precipitation (April–June)	−0.00087***	−0.00076***
	(0.00018)	(0.000158)
Precipitation (July–September)	0.0004**	0.0005812**
	(0.00017)	(0.000234)
Maximum temperature^2 (April–June)	0.0007646	
	(0.0007243)	
Maximum temperature^2 (July–September)	−0.0018092**	
	(0.00007681)	
Minimum temperature^2 (April–June)		0.00034146
		(0.0004041)
Minimum temperature^2 (July–September)		−0.00055802
		(0.00037749)
Precipitation^2 (April–June)	0.00000062***	0.00000055***
	(0.00000014)	(0.00000012)
Precipitation^2 (July–September)	−0.00000045*	−0.00000057**
	(0.00000023)	(0.0000002805)
Trend	Yes	Yes
Trend^2	Yes	Yes
Regional fixed effects	Yes	Yes
Observations	380	380
R^2	0.09	0.06
AIC	−171.3147	−158.846
BIC	−131.913	−119.4443
F Statistic	3.71385***	2.46417***

(***), (**), and (*) indicate significance at 1%, 5%, and 10% respectively. Reported values are estimated coefficients, while robust standard errors are in parentheses.

temperatures positively and significatively affect grapevine productivity (with a semielasticity of about 0.1166), as heat promotes ripening and sugar accumulation. However, also in this case, the association is nonlinear (the quadratic term is negative with a semielasticity of about −0.0018), suggesting that the positive effect decreases when very high temperatures occur. During the veraison and ripening phases, grapes are vulnerable to excessive heat, which can reduce berry size and sugar accumulation, negatively affecting yield and increasing economic losses, due to lost earnings or a decline in quality. For instance, at about 33°C a further 1°C increase in maximum temperature is associated with an approximate 0.3% reduction in grapevine productivity.

In Model 2b, the semi-elasticities for minimum temperatures are not statistically significant, while precipitation from the April to June (s_1) have significant negative semielasticity, whereas the quadratic effect is positive in both specifications, suggesting that very high amounts of precipitation may not be so harmful. From the July to September (s_2) while moderate rainfall supports berry growth and prevents water stress during veraison and ripening, excessive precipitation can lead to berry swelling, increased risk of disease, and dilution of sugars, which can adversely affect productivity in the final stages before harvest, causing economic losses for farmers. This finding is confirmed in both Model 2b (with minimum temperatures) and Model 2a (with maximum temperatures), the latter providing the best overall fit (highest R^2, lowest AIC), supporting this evidence.

Results from standardized specification of the weather

Unlike Table 4, where the coefficients measure the impact of an absolute unit change (e.g., 1°C), standardized weather indexes specification (iii) is represented in Table 5, where maximum and minimum temperature and precipitation indexes capture deviations from long-term regional means. This approach allows for a direct comparison of different weather factors, regardless of their units of measurement. In the standardized index specification (Table 5), anomalies in maximum temperature from April to June in model (3a) are not statistically significant, suggesting that moderate interannual fluctuations in spring heat, around the local climatic norm, do not systematically affect grapevine productivity once other controls are included. By contrast, positive anomalies in maximum temperature from July to September have a negative and significant effect: a one-standard-deviation increase in the summer maximum temperature index reduces productivity by about 2%. This result is consistent with the idea that, during veraison and ripening, unusually hot summers push conditions beyond the agronomically favorable range, increasing the likelihood of heat stress and negatively affecting yields. Minimum temperature indices, in model (3b), in both seasons are not statistically significant, indicating that, when measured as standardized anomalies, deviations in minimum temperatures around their long-term seasonal averages play a limited role in explaining interannual productivity fluctuations at the regional scale.

Precipitation anomalies display a clearer seasonal pattern. The standardized precipitation index for s_1 is negative and highly significant: a one-standard-deviation increase in spring rainfall is associated with a reduction in productivity of around 1.8–1.9%. This suggests that springs that are markedly wetter than usual tend to be unfavorable for grapevine, likely because excess moisture in early phenological stages favors disease

Table 5 Regression results: log grapevine productivity estimation in a standardized weather indexes specification. Source: Author's elaborations on ISTAT and JRC Agri4cast MARS Meteorological Database

Dependent variable:	**Log grapevine productivity**	
	(3a)	**(3b)**
Std max temp index (April–June)	0.003692	
	(0.004039)	
Std max temp index (July–September)	−0.02004**	
	(0.00781)	
Std min temp index (April–June)		0.0004
		(0.0038)
Std min temp index (July–September)		−0.0024
		(0.0032)
Std precipitation index (April–June)	−0.01934***	−0.0178***
	(0.00548)	(0.0004)
Std precipitation index (July–September)	0.007188*	0.01107***
	(0.00395)	(0.00396)
Trend	Yes	Yes
$Trend^2$	Yes	Yes
Regional fixed effects	Yes	Yes
Observations	380	380
R^2	0.08	0.06
AIC	−200.0423	−191.0635
BIC	−176.4013	−167.4225
F Statistic	5.34952***	3.91692***

(***), (**), and (*) indicate significance at 1%, 5%, and 10% respectively. Reported values are estimated coefficients, while robust standard errors are in parentheses.

pressure and interferes with optimal vegetative and reproductive development. In contrast, the precipitation index in s_2 is positive and significant, implying that, in the generally drier summer period, additional rainfall relative to the long-term mean tends to support productivity. This finding is consistent with the notion that moderate increases in summer moisture can alleviate water stress and sustain berry growth, although the quadratic results in Table 4 indicate that very wet summers may still become detrimental.

Results from degree days specification of the weather

Finally, the degree days specification (iv), based on GDD, KDD and FDD over the April–September growing season, is reported in Table 6 and in Table 8 in Appendix C. The table 6 presents the preferred specification, corresponding to the combination of thresholds that delivers the most robust and significant results, while Table 8 documents the full set of robustness checks in which the upper threshold separating GDD from KDD and the lower threshold defining FDD are systematically varied. Specifically, the upper bound for GDD is gradually increased from 27°C to 33°C (with a fixed lower bound at 10°C), and KDD is defined as exposure above each corresponding upper threshold. In parallel, a sequence of FDD indicators is constructed for progressively colder thresholds, from 3°C down to –3°C.

Table 6 Regression results: log grapevine productivity estimation in a degree days specification. Source: Author's elaborations on ISTAT and JRC Agri4cast MARS Meteorological Database

Dependent variable:	**Log grapevine productivity (4 g)**
GDD 10–33°C (April–September)	0.000141*
	(0.000077)
KDD above 33°C (April–September)	−0.00098***
	(0.00037)
FDD below −3°C (April–September)	−0.00087*
	(0.00050)
Precipitation (April–September)	0.0007***
	(0.00022)
Precipitation^2 (April–September)	−0.00000072**
	(0.00000029)
Trend	Yes
Trend^2	Yes
Regional fixed effects	Yes
Observations	380
R^2	0.06
AIC	−162.8917
BIC	−135.3105
F Statistic	3.2809***

(***), (**), and (*) indicate significance at 1%, 5%, and 10% respectively. Reported values are estimated coefficients, while robust standard errors are in parentheses.

Across all models, the GDD coefficients are positive, but they become statistically significant only when the upper threshold is set at 31°C or higher (specifications 4e–4 g). This pattern suggests that allowing a relatively wide beneficial temperature range, approximately between 10°C and 31°C, better captures the response of grapevine productivity to growing season heat in Italy. As the upper bound increases from 31°C to 33°C, the magnitude of the GDD coefficient stabilizes and model fit gradually improves, as indicated by increasing R^2 and decreasing AIC and BIC. This supports the choice of the 10–33°C interval as a plausible and empirically supported thermal window for productive heat accumulation.

Table 6 reveals that KDD coefficients are negative for all thresholds and become statistically significant from 30°C upwards, with their absolute value growing as the upper bound increases. This indicates that exposure to temperatures above 30°C is generally harmful and that the marginal damage intensifies at more extreme temperature levels: the detrimental impact is relatively moderate just above 30°C, but becomes much larger once temperatures frequently exceed 32–33°C. These results are consistent with the nonlinear pattern found in the quadratic specification and with the main model in Table 6, reinforcing the interpretation that grapevine productivity benefits from warming up to 30°C but declines beyond that point.

FDD coefficients are also negative for all cold thresholds but are statistically significant only for the most stringent threshold (below –3°C). This suggests that small or moderate cold anomalies during the growing season are not sufficient to generate detectable yield effects at the regional scale, whereas rare but intense frost episodes (captured by FDD below −3°C) have a clear and sizeable negative impact on productivity. Precipitation and its square are stable across all specifications, with a positive linear term and a negative quadratic term, confirming the concave relationship between cumulative rainfall and productivity already documented in the main models: moderate rainfall is beneficial, while very wet growing seasons reduce yields. The negative and significant coefficient confirms that extreme higher or colder temperatures generate net economic losses. Any increase in degree days above 31–33°C or below −3°C leads to yield drops (fewer quintals/ha) and potential qualitative damage (reduced sugar content, loss of acidity, aromatic imbalances).

Interpreting the degree days coefficients in Table 6, an additional 10 KDD units above 33°C implies a 1% reduction, and an additional 10 FDD units below −3°C implies about a 0.9% reduction in productivity. The economic impact therefore translates into lower direct revenues (quantity produced), a lower unit price (lower quality), and increased insurance and risk management costs.

Discussion

The results highlight three main findings:

(i) Seasonally differentiated impacts of growing-season weather, especially for maximum temperatures and precipitation between April–June and July–September;
(ii) Nonlinear temperature effects, with grapevine productivity increasing with heat up to roughly 31–33°C but declining under extreme heat;
(iii) Pronounced yield sensitivity to severe frost events as captured by FDD indicator.

Overall, the evidence points to strong nonlinearities in the weather–productivity relationship, which are visually confirmed in Fig. 2, where the second-degree polynomial fit is provided between key weather variables and log grapevine productivity. The left-hand panel of the figure displays the relationship between maximum temperature from April to September and log grapevine productivity, suggesting a concave shape: productivity initially increases with temperature, then starts to decline beyond a certain threshold. The graph on the right shows a similar inverted-U relationship for precipitation, moderate rainfall appears to enhance productivity, but excessive precipitation leads to a decline. These patterns confirm the presence of significant non-linearities in the effect of

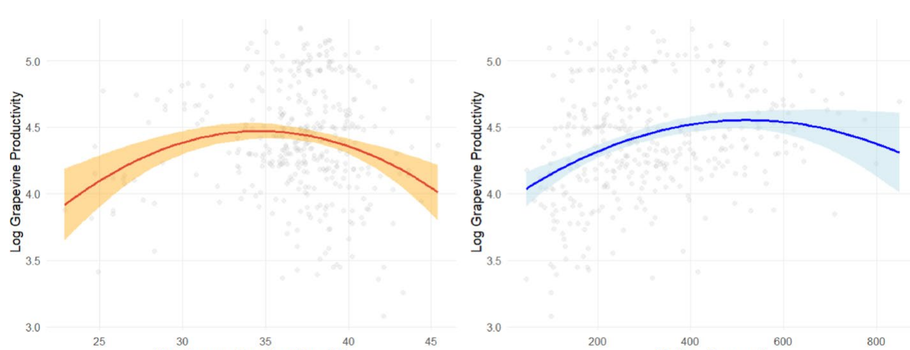

Fig. 2 Polynomial relationship between weather variables and log grapevine productivity (Apr-Sep)

both temperature and precipitation on grapevine productivity, justifying the adoption of a quadratic specification in the main analysis. The fitted values and confidence intervals (95%) were then plotted over the observed values. This evidence points out the marginal effects of weather variables across their full empirical distribution.

Moreover, the division of the growing season into two sub-periods, April–June (s_1) and July–September (s_2), plays a crucial role in uncovering these patterns. The econometric results show that coefficients for maximum temperature and precipitation differ markedly between s_1 and s_2, in line with the distinct phenological phases of vine development. Early-season conditions affect budbreak, flowering and fruit set, whereas late-season conditions are more relevant for veraison and ripening. Ignoring this seasonal differentiation would overlook important heterogeneities in the response of productivity to weather shocks. A further contribution of this research is the identification of appropriate temperature intervals for the degree days indicators. Robustness checks on alternative bounds for GDD, KDD and FDD show that the most informative specification is obtained when the upper threshold for heat exposure is set around 33°C and the frost threshold around −3°C, highlighting the temperature range within which extreme heat and severe frost become economically relevant for Italian grapevine yields. These findings are consistent with the broader evidence of climate pressure on European viticulture. Recent OIV statistics show that EU wine production has experienced a marked decline and increasing interannual variability since the early 2000 s (Fig. 3), with 2023–2025 volumes among the lowest of the last quarter century (International Organisation of Vine and Wine 2025).

The results also align with previous studies on Italian viticulture and weather variability (Accetturo and Alpino 2023; Moriondo et al. 2011; Sacchelli et al. 2017), which indicate the potential risk of a reduction in productivity when extreme heat and excessive precipitation interfere with grape development, leading to a lower overall yield. In particular, the standardized-index specification indicates that unusually hot summers generate a more marked negative economic impact than a spring heat wave, making the months of July to September the period of greatest economic risk, with the risk of fluctuations in revenues and grape quality (and therefore prices). Italian grapevine productivity appears to be more sensitive to temperature anomalies than to rainfall anomalies. This does not imply that precipitation is not an important factor, but rather that its economic impact may be more closely tied to long-term conditions. Overall, the empirical

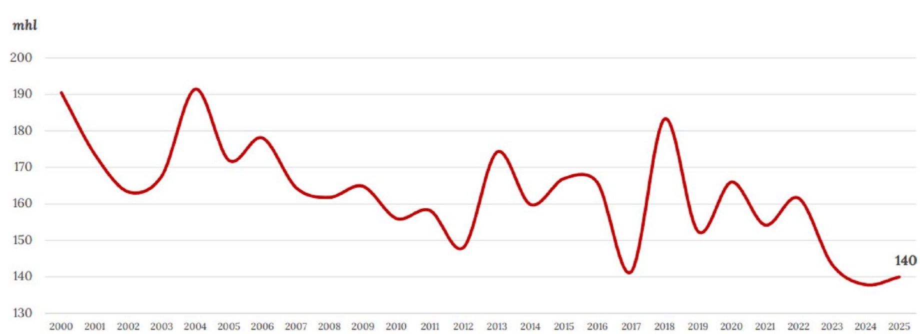

Fig. 3 Wine production in the EU, 2000–2025

evidence in Tables 4, 5 and 6 suggests direct implications for agricultural and insurance policy:

(i) Strengthening climate insurance instruments, as the results justify the need for weather-indexed policies based on anomalous temperature and rainfall thresholds (e.g., days above 31–33°C or standard deviations from the historical average), which could reduce the volatility of agricultural incomes;
(ii) Extending subsidies to climate insurance policies and encouraging participation in southern regions, where weather variability is greater and insurance coverage is still limited (Fusco et al. 2018);
(iii) Agronomic innovation and preventive investments, given that the economic effects of spring overheating and summer heatwaves are already observable.

From an economic perspective, the estimated percentage effects are far from negligible at aggregate scale. For illustration, applying a 1% yield reduction to a recent level of Italian wine production of about 47 million hectoliters implies roughly 0.5 million hectoliters of lost output, i.e. more than 60 million standard 0.75-litre bottles (International Organisation of Vine and Wine 2025). This underscores the relevance of our findings not only for grape-growers and wineries, but also for policymakers and insurance companies designing climate-risk management instruments.

Conclusions

Using a vine growth cycle-based aggregation method for growing-season weather variables, this paper documents how rainfall and minimum and maximum temperatures are associated with grapevine productivity in Italy at the regional level over the period 2006–2024. The focus of the undertaken analysis is on possible nonlinear effects of weather variables on grapevine productivity, that are investigated with the support of an original reconstruction of two agro-meteorological indicators.

The results show that the effects of weather variables, namely high and low temperatures and precipitations, on productivity vary according to the two growing seasons, April to June and July to September. Our empirical strategy captures the impact on grapevine productivity of deviations from the long-term productivity, driven by positive or negative anomalies in maximum and minimum temperatures and precipitation. Finally, the nonlinear relationship is confirmed by the estimates based on the GDD, KDD and FDD.

Overall, the results indicate that grapevine productivity benefits from higher temperatures during the growing season, while extreme heat sharply reduces yields, especially in the season from July to September. Generally, grapevine yield in Italy appears relatively resilient to warming up to 30°C, but a detrimental effect emerges once temperatures frequently exceed approximately 31–33°C, in line with Accetturo and Alpino (2023). The FDD indicator shows that severe frost events (temperatures below −3 °C during the growing season) are associated with considerable yield losses, confirming the sensitivity of vines to damaging cold spells. As to the effect of precipitations, moderate precipitation is found to be beneficial for productivity in the summer months, helping to alleviate water stress, while excessive rainfall, exerts a negative impact.

However, our analysis does not estimate region-by-region response functions and cannot capture local microclimatic effects at sub-regional scales; exploring heterogeneous responses across northern, central and southern regions, or across agro-climatic clusters, is therefore left for future research.

In addition, extending the analysis to a multi-country setting, or comparing region- and cultivar-specific temperature thresholds across major wine-producing countries, represents a natural extension of this work. To this end, further research could explore higher-resolution data, such as provincial-level analyses, and extend the methodology to include forecasting models aimed at estimating future productivity under different climate scenarios. Such developments would offer valuable insights for long-term adaptation strategies in the wine sector.

Finally, a research extension should address the improved understanding of how weather fluctuations impact the insurance market, affecting the insurance premiums paid by farmers and the insured value of crops. A better understanding of how different crops respond to extreme weather events could help explain why farmers differ in their demand for insurance against climate-related losses. Translating the yield effects estimated in this paper into a full economic assessment of their consequences for farm incomes, wine prices and regional value added is therefore an important avenue for future research.

Appendix A Time-series evidence for standardized weather indexes

See Figures 4, 5 and 6

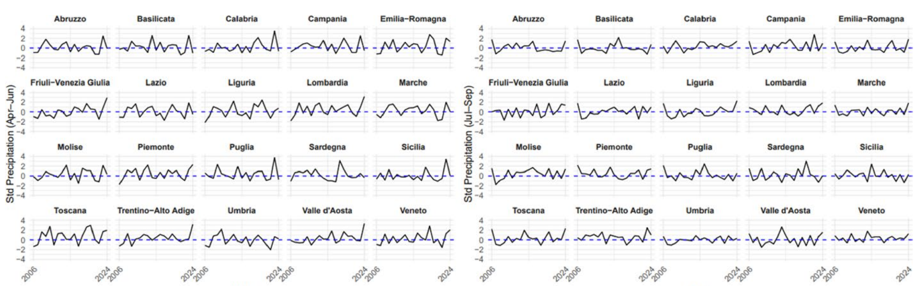

Fig. 4 Standardized precipitation for Italian regions (Apr-Jun vs Jul-Sep, 2006–2024)

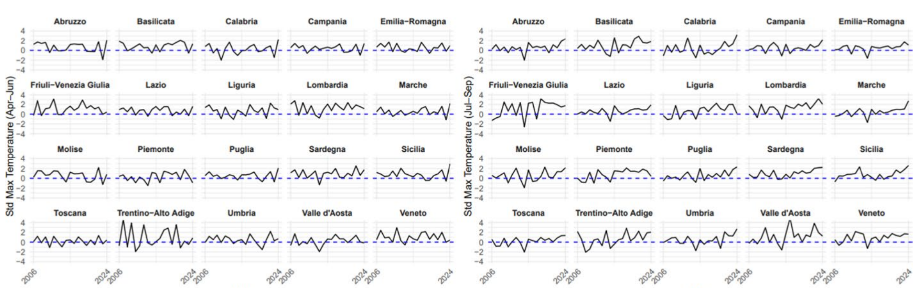

Fig. 5 Standardized maximum temperature for Italian regions (Apr-Jun vs Jul-Sep, 2006–2024)

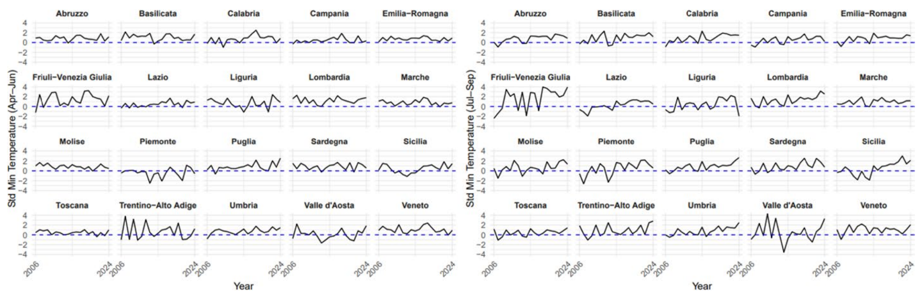

Fig. 6 Standardized minimum yemperature for Italian regions (Apr-Jun vs Jul-Sep, 2006–2024)

Appendix B Time-series evidence for grapevine productivity and growing-season weather

Figure 7 depicts the evolution of regional grapevine productivity in Italy from 2006 to 2024, measured as annual grape production per hectare of vineyard area under vine cultivation (q/ha). It is possible to compare the patterns across regions: Puglia, Veneto and Emilia-Romagna show the highest productivity levels, which remain persistently high during the entire period considered. In regions such as Molise and Friuli-Venezia Giulia, an increase in productivity is observed. While in Umbria and Liguria, grapevine productivity shows a decreasing pattern. Some regions show significant year-to-year variability, such as Basilicata and Calabria, where marked peaks and drops in productivity are observed. These differences may reflect the combined effects of climate conditions and other regional factors on yields. As depicted in Fig. 7, the 2017 harvest in Italy was characterized by a significant reduction in production (−26% compared to 2016). The unusual weather pattern with a dry and mild winter, an early budbreak of the vine that led to damage from late frosts, but also a consistent drought and localized episodes of hail caused lower yields in all Italian regions as well as a considerable premature harvest.

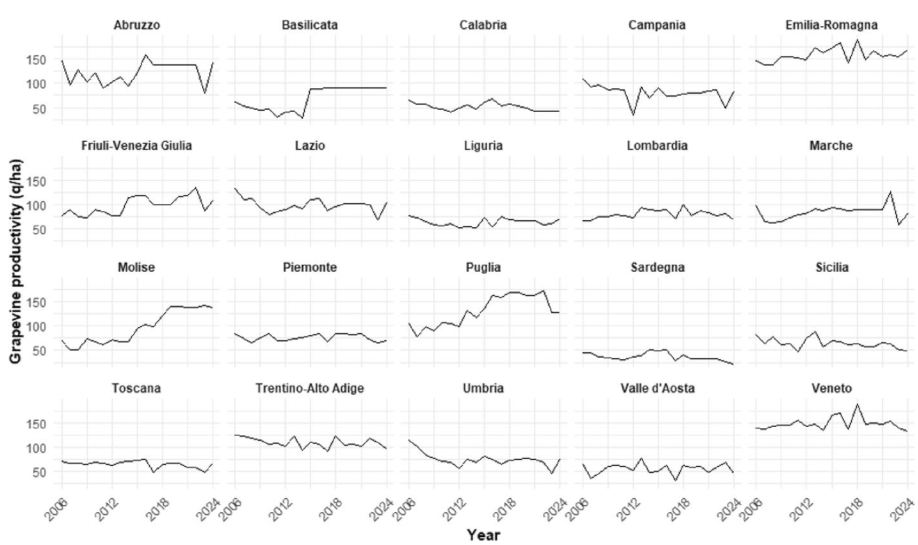

Fig. 7 Regional grapevine productivity (q/ha) in Italy, 2006–2024

Viticulture is also influenced by short-term fluctuations, such as intra-seasonal variability and daily oscillations in extreme temperatures during a particular season (Cohen et al. 2012). Figures 8, 9 and 10 report the regional time series of April–September average maximum and minimum temperatures and total precipitation, respectively, in Italy over 2006–2024, based on daily observations from the JRC MARS Agro-Meteorological Database aggregated at the regional scale. In each panel, the black line plots the annual growing-season (April–September) values at the regional level. The blue horizontal line denotes the region-specific long-term average over the entire baseline period. The red dashed lines represent a 90% reference band computed around the long-term mean.[4] Their purpose is to summarize historical interannual variability and visually identify

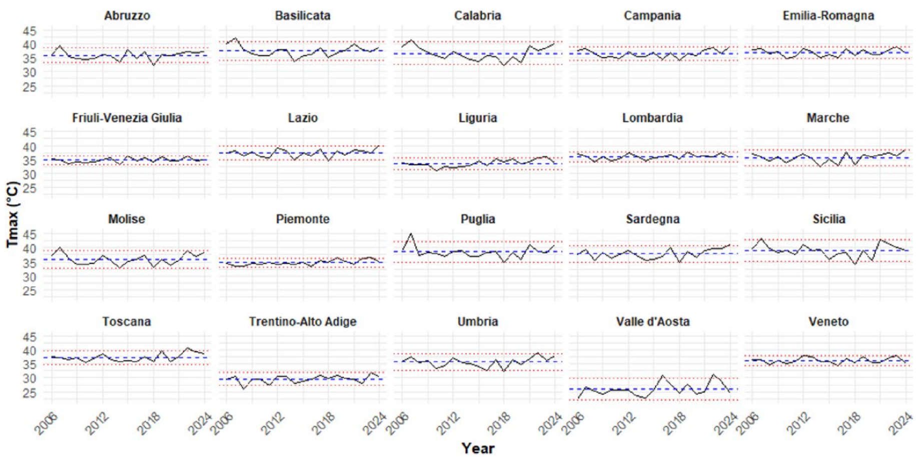

Fig. 8 Regional time series of growing-season (April–September) average maximum temperatures in Italy, 2006–2024

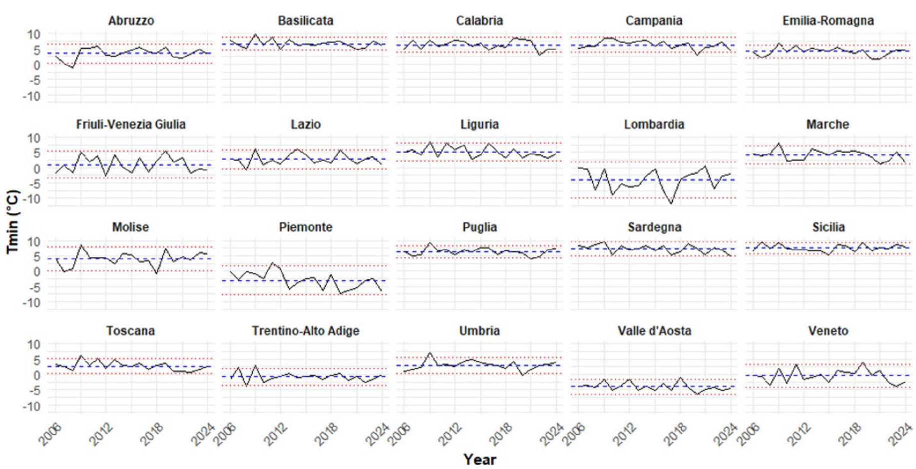

Fig. 9 Regional time series of growing-season (April–September) average minimum temperatures in Italy, 2006–2024

[4] The red dashed lines are descriptive reference bands, not confidence intervals from a trend estimation. For each region i, they are computed as $\bar{x}_i \pm 1.645\,\sigma_i$, where $\bar{x}_i$ and σ_i are the long-run mean and standard deviation of the April–September series over 2006–2024. No formal trend test (e.g., Mann–Kendall, Sen's slope) is associated with these bands.

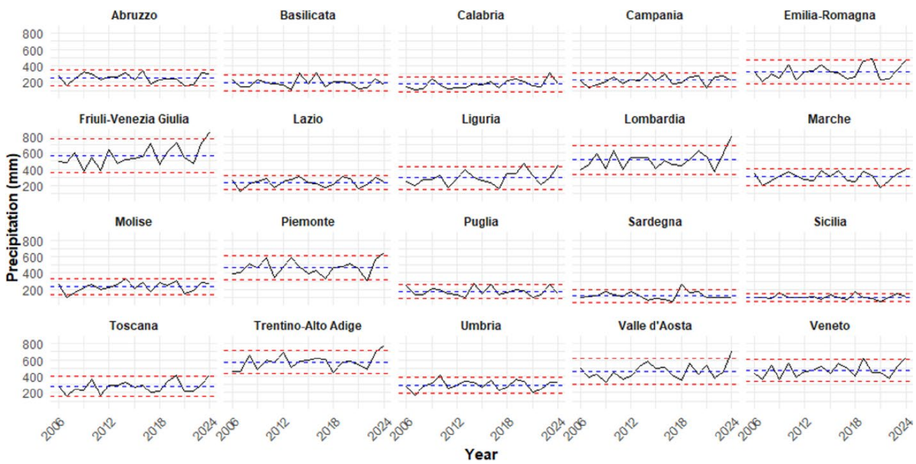

Fig. 10 Regional time series of cumulative growing-season (April–September) average precipitation in Italy, 2006–2024

anomalous years. These bands are purely descriptive and are used to highlight years with unusually high/low temperature or precipitation relative to historical variability. Over the 2006–2024 period, the growing-season temperature series display a clear interannual variability around region-specific historical means, with a tendency toward warmer conditions in most regions. In several cases, recent years lie persistently close to, or above, the upper bound of the 90% reference band, signaling unusually warm seasons relative to the local baseline. Occasional peaks beyond the red dashed lines indicate extreme heat episodes, which are agronomically relevant because they may accelerate phenological development and compress ripening, potentially exposing vines to heat stress during sensitive stages of berry growth and maturation. Minimum temperatures increase more mildly and remain mostly within the reference band; nevertheless, their upward displacement in several regions implies a reduced probability of damaging late-spring cold events, however some peaks exceed the reference bound. In Fig. 10, precipitation is markedly more volatile than temperature across all regions, oscillating widely around the long-term mean without a uniform monotonic pattern over the sample period. The water balance is primarily influenced by supply factors (1) local precipitation, and (2) ambient atmospheric humidity (Gambetta 2016). However, some peaks exceed the confidence bands, indicating anomalous precipitation events.

Appendix C Complementary results

See Tables 7 and 8

Table 7 Regression results: log grapevine productivity estimation in a weather linear specification. Source: Author's elaborations on ISTAT and JRC Agri4cast MARS Meteorological Database

Dependent variable:	**Log grapevine productivity**	
	(1a)	**(1b)**
Maximum temperature season April–June	0.0017	
	(0.0038)	
Maximum temperature season July–September	−0.0168**	
	(0.0071)	
Minimum temperature season April–June		0.0024
		(0.0031)
Minimum temperature season July–September		−0.0010
		(0.0039)
Precipitation season April–June	−0.0005***	−0.0005***
	(0.0001)	(0.0001)
Precipitation season July–September	0.0002	0.0003
	(0.0002)	(0.0002)
Trend	Yes	Yes
$Trend^2$	Yes	Yes
Regional fixed effects	Yes	Yes
Observations	380	380
R^2	0.06	0.05
AIC	−167.31	−159.72
BIC	−143.67	−136.01
F Statistic	4.193***	2.928***

(***), (**), and (*) indicate significance at 1%, 5%, and 10% respectively. Reported values are estimated coefficients, while robust standard errors are reported in parentheses.

Table 8 Regression results: log grapevine productivity estimation in a degree days specification

Dependent variable:	Log vine productivity						
	(4a)	**(4b)**	**(4c)**	**(4d)**	**(4e)**	**(4f)**	**(4 g)**
GDD 10–27°C (Apr–Sep)	0.000124						
	(0.000101)						
GDD 10–28°C (Apr–Sep)		0.0001185					
		(0.0000918)					
GDD 10–29°C (Apr–Sep)			0.0001213				
			(0.0000867)				
GDD 10–30°C (Apr–Sep)				0.0001292			
				(0.0000842)			
GDD 10–31°C (Apr–Sep)					0.000138*		
					(0.0000826)		
GDD 10–32°C (Apr–Sep)						0.000141*	
						(0.0000807)	
GDD 10–33°C (Apr–Sep)							0.000141*
							(0.000077)
KDD above 27°C (Apr–Sep)	−0.0001909						
	(0.0001756)						
KDD above 28°C (Apr–Sep)		−0.0002285					
		(0.0001837)					
KDD above 29°C (Apr–Sep)			−0.0002865				
			(0.0001980)				
KDD above 30°C (Apr–Sep)				−0.0003762*			
				(0.0002210)			
KDD above 31°C (Apr–Sep)					−0.000509**		
					(0.0002530)		

Table 8 (Continued)

Dependent variable:	Log vine productivity						
	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)	(4 g)
KDD above 32°C (Apr–Sep)						−0.000696**	
						(0.0003000)	
KDD above 33°C (Apr–Sep)							−0.00098***
							(0.0003700)
FDD below 3°C (Apr–Sep)	−0.0000991						
	(0.000137)						
FDD below 2°C (Apr–Sep)		−0.0001247					
		(0.0001584)					
FDD below 1°C (Apr–Sep)			−0.0001598				
			(0.0001894)				
FDD below 0°C (Apr–Sep)				−0.0002192			
				(0.0002300)			
FDD below −1°C (Apr–Sep)					−0.00033		
					(0.0002900)		
FDD below −2°C (Apr–Sep)						−0.00052	
						(0.0003800)	
FDD below −3°C (Apr–Sep)							−0.00087*
							(0.0005000)
Precipitation (Apr–Sep)	0.00064***	0.000648***	0.000658***	0.000672***	0.000685***	0.000692***	0.0007***
	(0.000232)	(0.000230)	(0.000230)	(0.000230)	(0.000230)	(0.000229)	(0.000220)

Table 8 (Continued)

Dependent variable:	**Log vine productivity**						
	(4a)	**(4b)**	**(4c)**	**(4d)**	**(4e)**	**(4f)**	**(4 g)**
Precipitation^2 (Apr–Sep)	−0.00000065**	−0.00000066**	−0.00000067**	−0.00000068**	−0.00000069**	−0.00000070**	−0.00000072**
	(0.00000029)	(0.00000029)	(0.00000029)	(0.00000029)	(0.00000029)	(0.00000029)	(0.00000029)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trend^2	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	380	380	380	380	380	380	380
R^2	0.04	0.04	0.04	0.04	0.05	0.05	0.06
AIC	−153.92	−154.30	−155.07	−156.39	−158.25	−160.38	−162.89
BIC	−126.34	−126.71	−127.49	−128.80	−130.67	−132.80	−135.31
F Statistic	2.03***	2.08***	2.19***	2.37***	2.63***	2.93***	3.28***

(***), (**), and (*) indicate significance at 1%, 5%, and 10%. Reported values are estimated coefficients, with robust standard errors in parentheses.

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Author contributions
Conceptualization was contributed by C.M, G.P.A., M.D.S., E.M and P.P.M; data selection, management, and analysis were involved by C.M; draft paper preparation was performed by C.M; review and editing was attributed by C.M., G.P.A., M.D.S., E.M and P.P.M.; supervision was done by E.M, and P.P.M. All authors have read and approved this version of the manuscript.

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Availability of data
No datasets were generated or analysed during the current study.

Declarations

Competing interests
The authors declare no Conflict of interest.

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